Net Promoter Score - Beyond the Measure: a Statistical Approach Based on Generalized Ordered Logit Models Implemented by Stata to conduct a NPS Key Drivers' Analysis

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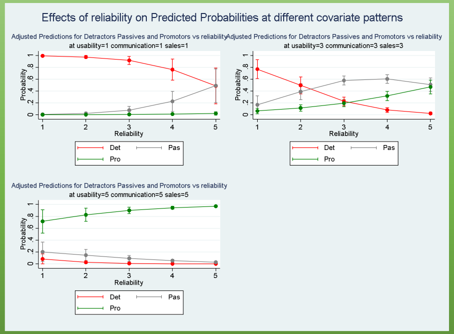

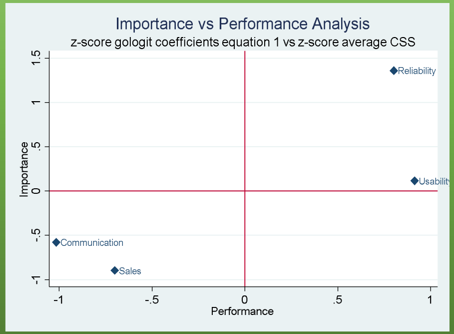

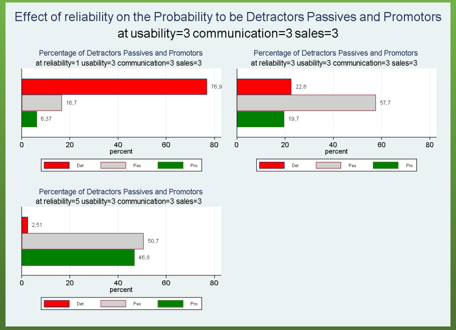

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Abstract

The Net Promoter Score (NPS) index is a popular satisfaction measure which allows one to gauge Customer Loyalty (CL) at most large and medium-size firms in different fields.
Because of its impact on company's growth line managers are strongly interested in knowing which factors can increase NPS by increasing promoters and decreasing detractors.
NPS Key Drivers' Analysis (NPS KDA) can be a suitable tool for this task.
A KDA may be conducted by implementing different statistical approaches, for identifying those factors or drivers with a significant impact on a specific outcome variable.
In the contest of NPS KDA, the Regression Models for ordinal outcomes represent a statistical approach for identifying those significant Customer Experience (CX) attributes which can drive Customer Status (CS) from detractors to promoters, leading companies to design appropriate improvement strategies, involving those facets of product or service with the highest improvement priority.
In this presentation the NPS KDA has been conducted by implementing in Stata two special cases of the Generalized Ordered Logit Models, the Proportional Odds Model (POM) and the Partial Proportional Odds Model (PPOM), where the dependent variable CS was modelled as function of different CX attributes.

Introduction

The Net Promoter Score Key Drivers' Analysis (**NPS KDA**) is typically based on statistical regression models which consider the customers' responses to the *likelihood to recommend question* as the dependent variable and the *Customer Satisfaction Scores* on different Customer Experience (CX) attributes as the independent variables [21].
One of the most common models used for this purpose is the Ordered Logit Model (OLM), also known as the Proportional Odds Model (**POM**) [18,26].
This model is based on a strong assumption on the regression coefficients, known as the Parallel-line Assumption or **Proportional Odds Assumption**.
Where the assumption is violated the Partial Proportional Odds Model (**PPOM**) can be used as an alternative model, allowing to relax the Proportional Odds Assumption just for those variables for which the assumption is violated.

In this study the NPS KDA has been conducted in the contest of the professional audio market by implementing in Stata two special cases of the Generalized Ordered Logit Models, the Proportional Odds Model (**POM**) and the Partial Proportional Odds Model (**PPOM**), where the dependent variable Customer Status (**CS**) was modelled as function of different **CX attributes**, in order to explore which facets of product/service have a significant impact on Customer Status, allowing line-managers to take focused improvement actions for increasing Customer Loyalty.

Considering that the results of nonlinear models as the POM and the PPOM, are not easy to interpret, especially in a business contest, **graphical tools** have been developed by Stata, for helping line-managers to interpret the results and design suitable improvement plans.

Summary

Net Promoter Score

- NPS - a measure of Customer Loyalty
- NPS Key Drivers’ Analysis

Models for Ordinal Outcomes

- OLM (ologit, POM)
- GOLM (gologit, PPOM)

Case Study

- Variables’ Description
- Descriptive Statistics
- Regression Analysis by *ologit* and *gologit2*
- *ologit* vs *gologit2* - LR test and information criteria (AIC and BIC)
- *ologit* vs *gologit2* - Table of coefficients

Model Interpretation - Tables and graphical tools by Stata

- Tables of Adjusted Predictions at specified covariate patterns
- Plots of Adjusted Predictions at specified covariate patterns
- Plots of Marginal Effects at specified covariate patterns
- Bar Charts of Adjusted Predictions at specified covariate patterns
- Importance vs Performance Analysis matrix

Reports for NPS KDA

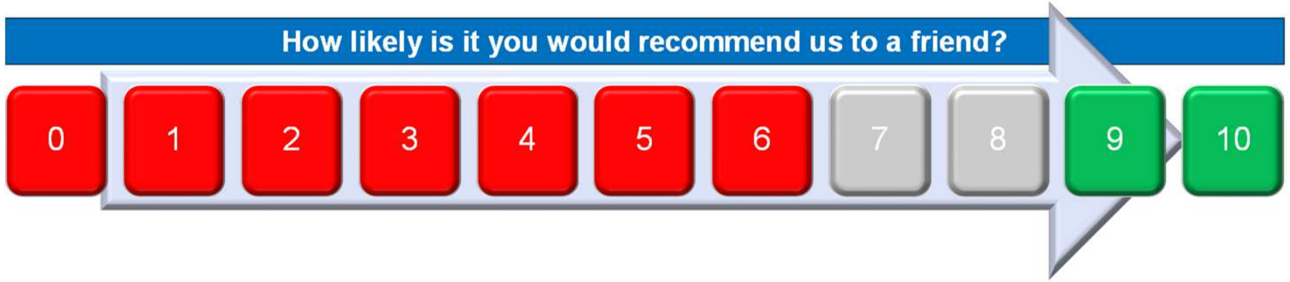
- Importance vs Performance Analysis matrix
- Bar Charts of Adjusted Predictions
- Plot of Marginal Effects

Conclusions

- Generalized Ordered Regression Models as a tool for implementing NPS KDA
- The PPOM as an alternative model to the POM to conduct a NPS KDA
- The PPOM allows to distinguish the uniform, increasing or decreasing effects of each facet of product/service
- Key Drivers’ Analysis Reports developed by Stata can support line-managers in interpreting the result

Net Promoter Score
- a measure of Customer Loyalty

In a more and more competitive environment the concept of **Customer Experience** (CX) is becoming very common, especially in those markets with a low product differentiation opportunities [21].
These companies adopt a CX program which is suitably designed including market research surveys, based on suitable and specific metrics, data collection plans, statistical data analysis processes and action plans for implementing the required operational improvements.
CX is strongly related to **Customer Loyalty** (CL). The first step of a CX program is to measure CL by suitably designed customer satisfaction surveys based on appropriate metrics.
In 2003 **Frederick Reichheld** proposed, as effective metric for measuring CL, the index known as **Net Promoter Score** (NPS), which gauges the customers' willingness to recommend the company to a friend or a colleague.
In his paper *The One Number You Need To Grow* [27], Reichheld shows how a single survey question can be a useful **predictor of growth**.
This question is known as *would recommend question* or ***likelihood to recommend question*** (**LTR question**), because it measures the customers' willingness to recommend the company or a product or service of the company to someone else (***On a zero-to-ten scale, how likely is it that you would recommend the company, the brand, or its products/services to a friend or a colleague***?).



Net Promoter Score
- a measure of Customer Loyalty

Reichheld and his colleagues **gathered and analyzed data on customers' behaviors**, as repeat purchases and referral patterns, in order to correlate the survey responses of individual customers of a company and those individuals' actual referral and purchase behaviors.
They decided for an **ordinal 11-point scale**, which ranged from 0 ("not at all likely") to 10 ("extremely likely"). By analyzing the customer referral and repurchase behavior along this scale they identified three clusters:

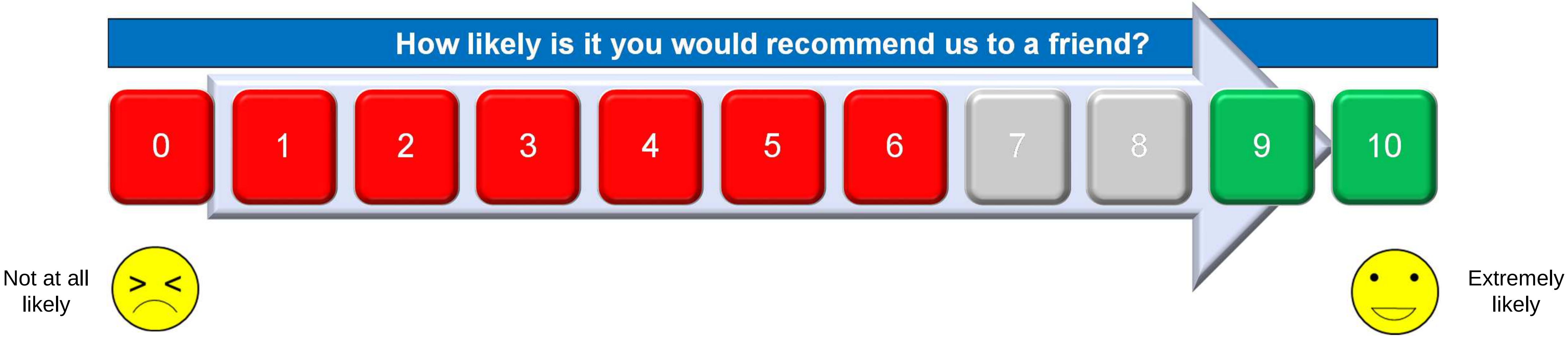
- ***PROMOTERS*** (Pro): those customers with the highest rates of repurchase and referral and who gave a rate of **9** or **10**
- ***PASSIVELY SATISFIED CUSTOMERS*** (Pas): those customers who gave a rate of **7** or **8**
- ***DETRACTORS*** (Det): those customers who gave a rate from **0** to **6**

The final step was **figuring out an index** called **NET PROMOTER SCORE**, given by subtracting the percentage of detractors from the percentage of promoters, and **correlating this index with the company's average growth rate for different industries**.

For most companies and most industries they found a **strong correlation** between **NPS** and **company's growth**, leading to the concept that
"***the only path to profitable growth lies in a company's ability to get its loyal customers to become, in effect, its market department***" [27].
This means that a company must not limit its effort to acquiring new customers, but it has to convert these new customers into loyal promoters.
In their study they found that those customers who give the most enthusiastic responses (9, 10) not only return to purchase again, but also recommend the brand to their friends or colleagues. A loyal customer is not just a customer who makes repeat purchases, but he also acts as a reference for the company by recommending its products/services [27].
This way **a loyal customer acts as an unpaid sales person who markets company's products or services and generates growth**.
It's very important to take into account the basic role of the enthusiastic customers (promoters) as external members of the marketing department.
At the same time, it is fundamental trying to **limit the bad word-of-mouth** focusing on those customers who refer a neutral or negative experience and immediately providing and action plan with suitable designed corrective actions.

It follows that **creating new promoters and fewer detractors**, that means **increasing the company's NPS**, and building the true loyalty represent a **path for a sustainable and profitable growth**.

Net Promoter Score
- a measure of Customer Loyalty



Detractors

- 0 – 6
- unsatisfied customers
- unlikely to recommend company/brand/products/services

Passives

- 7 – 8
- generally satisfied customers but not necessary loyal

Promoters

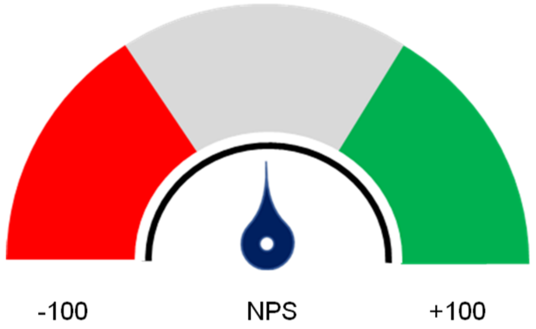
- 9 – 10
- external market department
- very likely to recommend company/brand/products/services
- they'll continue using products/services

Net Promoter Score
- a measure of Customer Loyalty

The NPS is defined as the ***difference between the percentage of promoters and the percentage of detractors***.
Based on the above definition, the NPS may range from -100 (every customer is a detractor) to +100 (every customer is a promoter) [21].

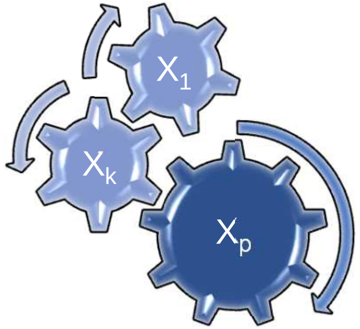
$$NPS = \left(\frac{N_{Pro} - N_{Det}}{N_{respondents}}\right) \times 100$$

$$NPS \in [-100; +100]$$



NPS is only a starting point!

Which are the underlying predictors of Customer Status???



NPS Key Drivers' Analysis
- Look beyond NPS

A well designed NPS survey should include not only the LTR question, but also other follow-up questions

The first result coming from a statistical analysis of a NPS survey is the NPS index measurement.
But it is very important to take into account that **this number alone is not significant** (it does not represent a real information for companies), because **line managers need to know which factors really affect NPS**, in order to develop suitable action plans for improving Customer Loyalty (CL).
The next step is to identify which Customer Experience (CX) attributes have the highest impact on NPS, and so the highest improvement priority in order to maximize this index [21].
A well designed NPS survey should include not only the LTR question, but also other **follow-up questions** where the respondents are asked to rate their satisfaction on particular **experience attributes** (facets of product or service). Depending on the specific design of the survey, the NPS survey may also include **demographic attributes** (age, gender, business or working area, job function).

Considering the high cost related to some improvement actions it is **fundamental to identify those CX attributes with significant impact on the overall NPS** by conducting a **Key Driver Analysis** (KDA) [9,15,16,18,21].
The Key Drivers' Analysis (KDA) allows business executives and line managers not only to **identify** those controllable factors (key drivers) which have significant effects on NPS, but also to **measure their impact**, so that they can increase promoters and reduce detractors with a consequent increase in NPS.

This type of KDA conducted for a satisfaction measure as the NPS is called **NPS Key Drivers' Analysis** (***NPS KDA***).
Companies implement the NPS KDA so as to **decide on how to allocate their investments** in specific Customer Experience (CX) attributes in order to **maximize the impact on the NPS**.
More over NPS KDA may be a tool for what if analysis so as to assess the impact of a change in a CX attribute satisfaction to the overall NPS.

Models for ordinal outcomes
- the Ordered Regression Models

An ordinal variable is a categorical variable where the categories can be ranked form a lower to a higher level.
In survey research it's very common to find questions where **respondents are asked to express their feeling with a statement**, by choosing between limited number of response categories ordered in a Likert scale (as, strongly agree, agree, neutral, disagree or strongly disagree).
Even if these variables have ordered categories, **the distance between the categories is unknown**.
In this case the strong assumption that the intervals between adjacent categories are equal and the use of **ordinary least square** (**OLS**) **regression** can lead to **misleading estimates** of the effects of the independent variables and to **inaccurate tests of statistical significance**, as shown by Richard D. McKelvey and William Zavoina (1975) [22], and also by Winship and Mare (1984) [37].
With ordinal outcomes it’s more appropriate to use models that avoid the assumption of an equal space between the ordered categories.

Many models have been developed for ordinal dependent variables, but one of the most popular models is the model commonly known as Ordinal Regression Model or **Ordered Regression Model (ORM)**, which includes two versions, the ***Ordered Logit Model*** and the ***Ordered Probit Model***.

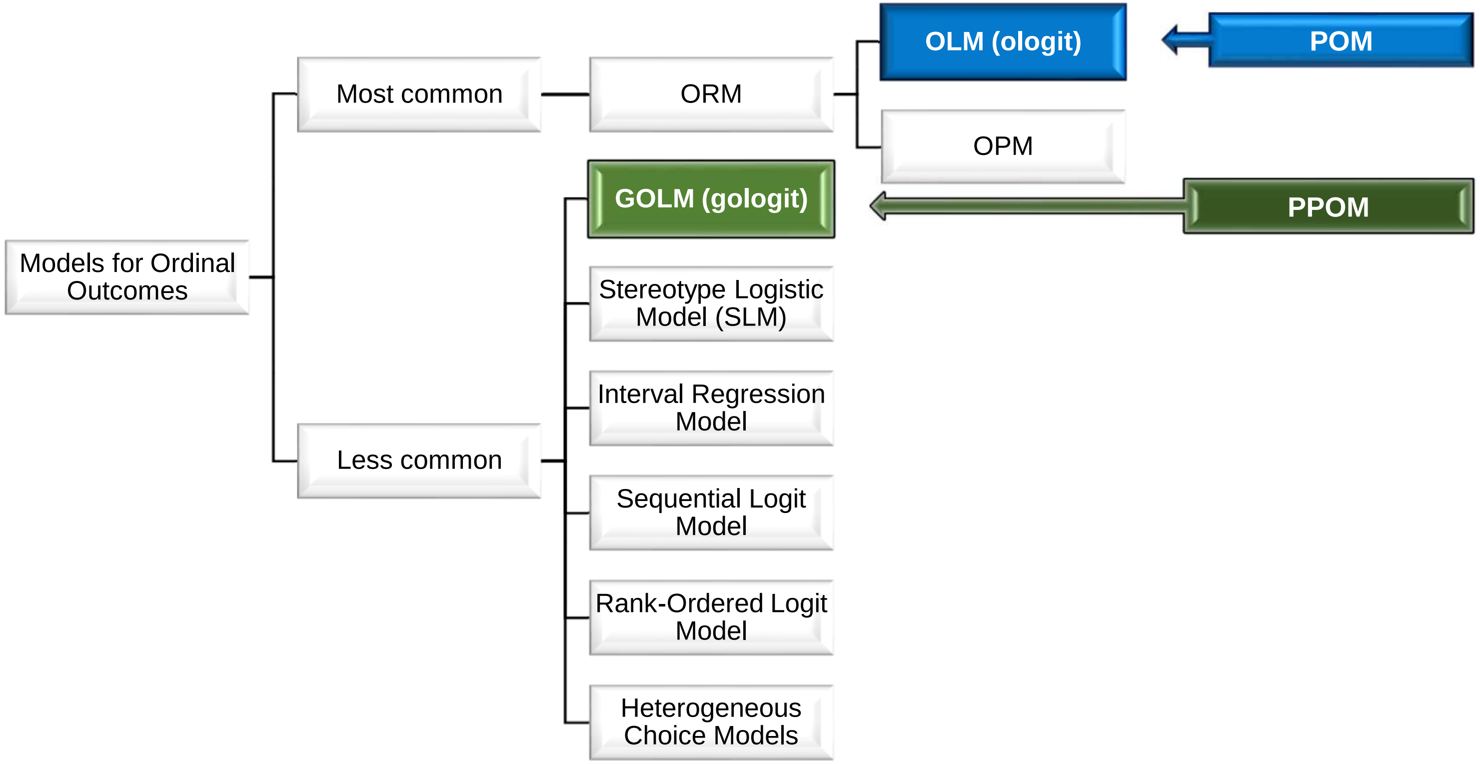
The ORM was introduced in **1975** by **McKelvey and Zavoina** in terms of an *underlying latent variable* [22].
The probit version was introduced by McKelvey and Zavoina (**1976**), while in **1980 McCullagh** introduced in biostatistics the logit version of the ORM, known as the ***Ordered Logit Model*** (**OLM**, or **ologit**), but also as ***Proportional Odds Model*** (**POM**), ***Cumulative Logit Model***, ***Parallel Lines Model***, ***Parallel Regression Model*** or ***Grouped Continuous Model*** (this name emphasizes the relationship between an underlying continuous latent variable and the observed, grouped variable).

Models for ordinal outcomes
- other Models

The ***Ordered Logit Model*** (**OLM**) and the ***Ordered Probit Model*** (**OPM**) are the most frequently used models for ordinal dependent variables in the social science, but there are other models also available [19,20,34].

One of the most popular alternative to the Ordered Logit Model is the ***Generalized Ordered Logit Model*** (**GOLM**, **gologit**) also known as ***Partial Proportional Odds Model*** (**PPOM**).

Other models for ordinal outcomes are the ***Stereotype Logistic Model*** (SLM), also known as Stereotype Ordered Regression Model [7], the ***Interval Regression Models***, also known as Grouped Regression Models (where a continuous variable is grouped at *known* values of cutpoints), the ***Sequential Logit Models***, the ***Rank-Ordered Logit Models*** (when respondents are asked to do several rankings), the ***Scoring Methods*** and the ***Heterogeneous Choice Models***, also known as Location-Scale Models.



The Ordered Logit Model

The Ordered Logit Model (**OLM**), also known as Proportional Odds Model (**POM**) or **ologit**, has the following structural model:

$$P(y_i \leq j|\boldsymbol{x_i}) = \frac{e^{(\tau_j - \boldsymbol{x}_i\boldsymbol{\beta})}}{1 + e^{(\tau_j - \boldsymbol{x}_i\boldsymbol{\beta})}} = \frac{1}{1 + e^{[-(\tau_j - \boldsymbol{x}_i\boldsymbol{\beta})]}} = \frac{1}{1 + e^{(-\tau_j + \boldsymbol{x}_i\boldsymbol{\beta})}} \qquad j = 1,2,\dots,J-1$$

The model can be written also as:

$$P(y_i > j|\boldsymbol{x_i}) = \frac{e^{(\boldsymbol{x}_i\boldsymbol{\beta} - \tau_j)}}{1 + e^{(\boldsymbol{x}_i\boldsymbol{\beta} - \tau_j)}} = \frac{1}{1 + e^{(\tau_j - \boldsymbol{x}_i\boldsymbol{\beta})}} \qquad j = 1,2,\dots,J-1$$

The logit equations are:

$$logit[P(y_i \leq j|\boldsymbol{x_i})] = ln\Omega_{\leq j|>j}(\boldsymbol{x_i}) = ln\left[\frac{P(y_i \leq j|\boldsymbol{x_i})}{P(y_i > j|\boldsymbol{x_i})}\right] = \tau_j - \boldsymbol{x}_i\boldsymbol{\beta}$$

$$logit[P(y_i > j|\boldsymbol{x_i})] = ln\Omega_{>j|\leq j}(\boldsymbol{x_i}) = ln\left[\frac{P(y_i > j|\boldsymbol{x_i})}{P(y_i \leq j|\boldsymbol{x_i})}\right] = \boldsymbol{x}_i\boldsymbol{\beta} - \tau_j$$

The minus before the linear predictor $\boldsymbol{x}_i\boldsymbol{\beta}$ is a consequence of the way the model is normally presented (as $logit[P(y_i \leq j|\boldsymbol{x_i})]$).
This way, increasing a covariate with a positive slope leads to a shift towards the right-end of the response scale, namely a rise of the probabilities of the higher levels and to a decrease of the probabilities of the lower outcomes.

The

The Generalized Ordered Logit Model

The Generalized Ordered Logit Model (**GOLM),** also known as Partial Proportional Odds Model (**PPOM**) or **gologit**, has been known about since at least the 1980s (e.g., McCullagh & Nelder, 1989; Peterson & Harrell, 1990), but recent advances in software, such as the user-written *gologit* [12] and *gologit2* [31] routines in Stata have made the model much easier to estimate and widely used.
When the assumptions of the ologit are violated some authors recommend the *mlogit* model.
Since *mlogit* ignores all the information about the ordering of categories → it estimates many more parameters making it less parsimonious and more difficult to interpret [31,33,34].
The gologit model can relax the Parallel-Line Assumption for those variables that violate it, while keeping the constraints on those variables that do not violate it.

The **GOLM** or **gologit** has the following structural model [31,33,34]:

$$P(y_i > j|\boldsymbol{x}_i) = \frac{\exp(\alpha_j + \boldsymbol{x}_i\boldsymbol{\beta}_j)}{1 + \exp(\alpha_j + \boldsymbol{x}_i\boldsymbol{\beta}_j)} \qquad j = 1,2,\ldots,J-1$$

The model can be written also as:

$$P(y_i \leq j|\boldsymbol{x}_i) = \frac{1}{1 + \exp(\alpha_j + \boldsymbol{x}_i\boldsymbol{\beta}_j)} \qquad j = 1,2,\ldots,J-1$$

The Generalized Ordered Logit Model

The **GOLM** provides *J*-1 logit equations where the betas changes across the cumulative logits.

An unconstrained gologit model provides results that are similar to what we get performing the Brant test by the Long & Freese SPost command *brant* [19], by running a series of logistic regressions where the ordinal variable has been collapsed into a dichotomy [31,33,34], but the simultaneous estimation of all equations causes results to differ slightly from when each equation is estimated separately [31].

This means that the GOLM provides *J*-1 panels where a positive coefficient for a predictor means that an increase in X makes it more likely for a respondent to be in a higher category, while a negative coefficient means that an increase in X makes it more likely for a respondent to be in the current category or in a lower one.

Where the Parallel-Line Assumption (PLA) is violated just for some independent variables the **PPOM** allows to relax the PLA just for the variables for which the assumption is violated.
The PPOM can be an alternative model where the Proportional Odds Assumption of the POM is violated.

The GOLM can not be interpreted in terms of an underlying continuous latent variable Y* [19,33]

- the gologit model can not appeals to the idea of an underlying continuous latent variable Y* [33], that accounts for the observed values of Y (anytime the Y* crosses a threshold the observed variable Y changes). This because of the structural model of gologit, which allows for more than one equation (each equation comes up with a different estimate of Y*).

The Generalized Ordered Logit Model

The Binary Logistic Model (**BLM**), the Proportional Odds Model (**POM**) and the Partial Proportional Odds Model (**PPOM**) are special cases of the unconstrained GOLM, and can be referred to this structural model, as follows:

$$P(y_i > j|\boldsymbol{x}_i) = \frac{\exp(\alpha_j + \boldsymbol{x}_i\boldsymbol{\beta}_j)}{1 + \exp(\alpha_j + \boldsymbol{x}_i\boldsymbol{\beta}_j)} \quad j = 1,2, \dots, J - 1$$

BLM

- special case of gologit model where $J = 2$

OLM or POM

- special case of the gologit model, where the coefficient vector $\boldsymbol{\beta}$ is the same across the logit equations

PPOM

- special case of the gologit model, where some of the betas can be the same for each *j*, while other can differ

The Generalized Ordered Logit Model
- Asymmetrical Effects

A key advantage of the **GOLM** is that the model allows to give evidence of asymmetrical effects that could be missed (obscured) or distorted if the POM were estimated [33].
In some cases the effects of an independent variable X on the response variable Y could differ across cumulative logits, leading to different magnitude of the effects and, sometimes, also to a different direction of the effect (opposite signs).
Examples of asymmetrical effects are provided by Williams [33].

Important relationship between X and Y might be obscured if a POM were used

GOLM can provide substantive insights on the underlying relationship that could occur between the response variable Y and those Xs where the Parallel-Line Assumption (PLA) is violated. In case of PLA violations the use of the POM could lead to misleading results and, sometimes, could also make the effects of some predictors not significant [33].

In these cases the GOLM could give evidence of a much more complex relationship where the effect of a predictor considerably differ in magnitude and also in direction.

Case study

Data source

The data used in this study come from a ***NPS Customer Satisfaction Survey*** conducted in **2019** by a ***professional audio company***.

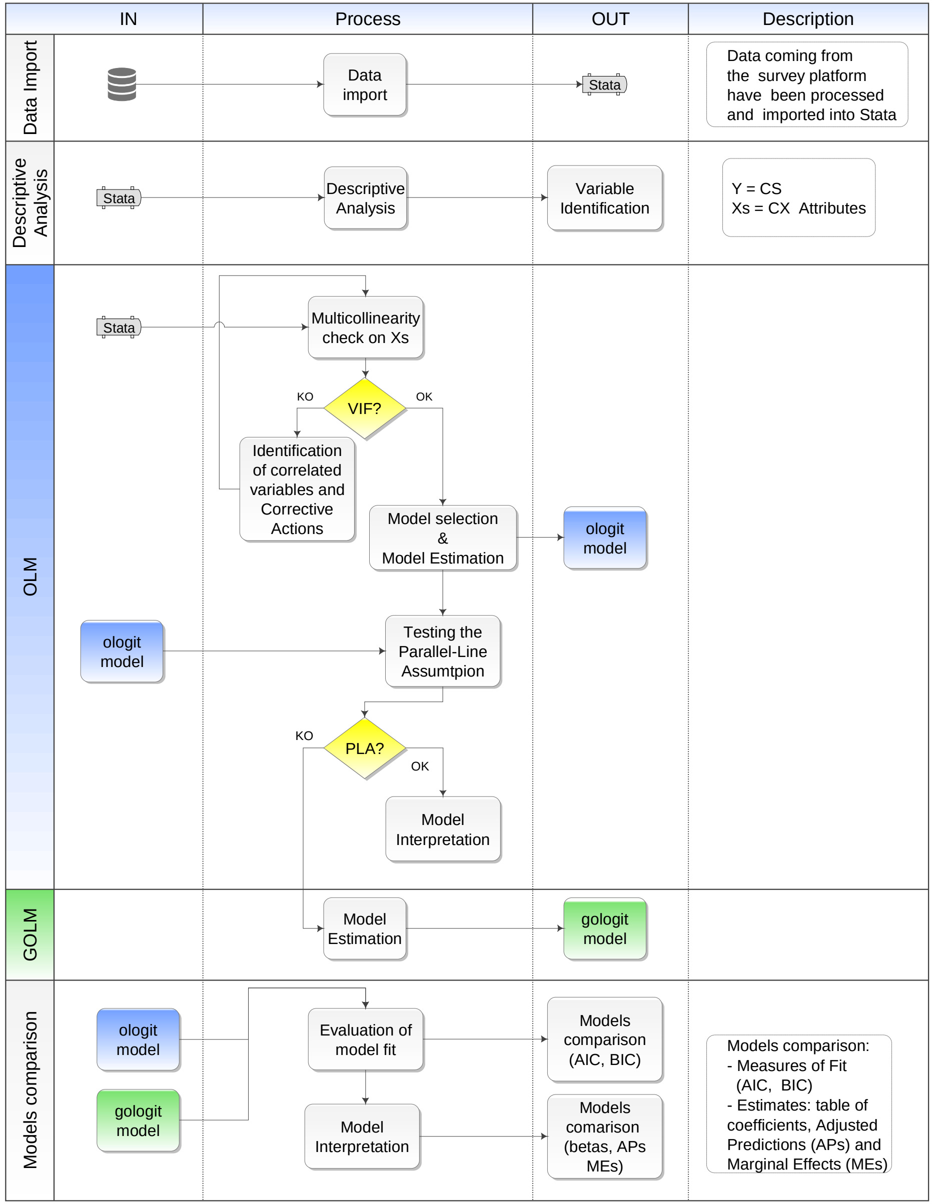
Data coming back form the survey (1.043 responses over 10.000 invitations) were suitably processed according to a structured data cleaning process, leading to a final sample of **773** records.

Software

The statistical analyses here referred have been implemented by ***Stata***: **Release 17** (1) and ***SPost13*** (Stata postestimation commands for version 13), a suite of programs for the postestimation interpretation of regression models for categorical outcomes, developed by J.S. Long and J. Freese [19].

Methods

In this study the NPS KDA has been conducted by implementing in Stata two special cases of the Generalized Ordered Logit Models, the Proportional Odds Model (**POM**) and the Partial Proportional Odds Model (**PPOM**), where the dependent variable Customer Status (**CS**) was modelled as function of different **CX attributes**.



(1) StataCorp. 2021. *Stata*: Release 17. Statistical Software. College Station, TX: StataCorp LLC. Stata is a registered trademark of StataCorp LLC.

Variables' description

ID	description	levels	LTR question and follow-up questions
CS (Customer Status)	ordinal variable with three levels	1 = Detractor (Det) 2 = Passive (Pas) 3 = Promoter (Pro)	How likely is it that you would recommend the company to a friend or colleague?
sales	Ordinal variable with 5 levels 1 = Extremely Unsatisfied 2 = Unsatisfied 3 = Neutral 4 = Satisfied 5 = Very Satisfied The responses to these questions measure the Customer Satisfaction Score (CSS) on different Customer Experience attributes (CX attributes)		Please rate your level of satisfaction with ***Relationship with Sales Network***
logistic			Please rate your level of satisfaction with ***Logistic and Delivery Time***
documentation			Please rate your level of satisfaction with ***Product Documentation***
packaging			Please rate your level of satisfaction with ***Quality Packaging***
look			Please rate your level of satisfaction with ***Look and Feel of the Products***
deployment			Please rate your level of satisfaction with ***Product Deployment***
usability			Please rate your level of satisfaction with ***Product Usability***
techsup			Please rate your level of satisfaction with ***Technical Field Support***
training			Please rate your level of satisfaction with ***Training Support***
service			Please rate your level of satisfaction with ***Service Center Support***
reliability			Please rate your level of satisfaction with ***Product Reliability***
information			Please rate your level of satisfaction with Access to ***Product Information***
communication			Please rate your level of satisfaction with ***Communication from the Company***

CS (Customer Status) is an ordinal variable with three levels or categories, Det (detractor), Pas (passively satisfied customer) and Pro (promoter), which shows an increasing ***latent score*** in terms of ***propensity to recommend the company***, and where the distances between adjacent categories may not be equal.
The ordinal nature of the outcome variable CS addresses to the implementation of a regression model as the Ordinal Logistic Model (OLM), to investigate the effect of different ***Customer Experience attributes*** (CX attributes), as underlying predictors of CS.

Customer Status as dependent variable

It's more meaningful for companies to know whether specific facets of product/service have significant effects on **converting Customers to higher Customer Status** than to know whether they have significant effects on increase the Customer Satisfaction Score along the whole scale [9].

Data coming back as responses to the LTR question are scores in a 11-point measurement scale, which represent the ***Customer Satisfaction Score*** (***CSS***). Starting form the CSS assigned by the respondents it is possible to measure their Customer Status (CS) as Detractors (Det), Passives or Passively Satisfied Customers (Pas) and Promoters (Pro).

CSS is an ordinal categorial variable with 11 categories (score from 0 to 10).
CS classifies the respondents into three categories according to their response (score) to the LTR question.
Also CS is an ordinal variable which shows an ordinality with an increasing latent value from the category Det, through the category Pas, to the category Pro.
Both CS and CSS are ordinal variables which could be included in the ORM equation as dependent variable.
Considering that the **final target** of the **NPS KDA** is to **easy communicate to line managers** which CX attributes require improvement actions for converting Det into Pro, so increasing the NPS, it's advisable to directly model as dependent variable **CS**, thus investigating the drivers to act on in order to **increase the percentage of Pro** and **decrease the percentage of Det**.
It would be of low importance to know how to increase the CSS from 0 to 3, or from 4 to 5, considering that, this way, the customer is still a detractor who hasn't any propensity to recommend the company, while rather she/he contributes to a negative word-of-mouth for the company.
That being said, a preliminary step before implementing the ORM consists of **recoding** the original variable directly generated by the LTR question (CSS) into the new variable CS, as indicated in this table.

LTR question → CSS → CS

CSS	***CS***	***description***
0 1 2 3 4 5 6	Det	Detractors
7 8	Pas	Passively Satisfied Customers
9 10	Pro	Promoters

CX attributes as independent variables

The Customer Satisfaction Survey was designed in order to obtain from the respondents their rating on different facets of product/service, by formulating suitable follow-up questions, where they were asked to assign their Customer Satisfaction Score (CSS) on a five-point Likert scale ranging from 1 = Extremely Unsatisfied to 5 = Very Satisfied to 13 Customer Experience (CX) attributes.

Follow-up questions
Please rate your level of satisfaction with ***Relationship with Sales Network***
Please rate your level of satisfaction with ***Logistic and Delivery Time***
Please rate your level of satisfaction with ***Product Documentation***
Please rate your level of satisfaction with ***Quality Packaging***
Please rate your level of satisfaction with ***Look and Feel of the Products***
Please rate your level of satisfaction with ***Product Deployment***
Please rate your level of satisfaction with ***Product Usability***
Please rate your level of satisfaction with ***Technical Field Support***
Please rate your level of satisfaction with ***Training Support***
Please rate your level of satisfaction with ***Service Center Support***
Please rate your level of satisfaction with ***Product Reliability***
Please rate your level of satisfaction with Access to ***Product Information***
Please rate your level of satisfaction with ***Communication from the Company***

sales	Ordinal variable with 5 levels 1 = Extremely Unsatisfied 2 = Unsatisfied 3 = Neutral 4 = Satisfied 5 = Very Satisfied The responses to these questions measure the Customer Satisfaction Score (CSS) on different Customer Experience attributes (CX attributes)
logistic	
documentation	
packaging	
look	
deployment	
usability	
techsup	
training	
service	
reliability	
information	
communication	

Descriptive Statistics

These 13 variables are ordinal variable with 5 levels (1 = Extremely Unsatisfied, 2 = Unsatisfied, 3 = Neutral, 4 = Satisfied ,5 = Very Satisfied) and measure in a five-point scale the Customer Satisfaction Score (CSS) on different Customer Experience attributes (CX attributes)

```
. sum sales logistic documentation packaging look deployment usability techsup training service reliability information communication CS
```

Variable	Obs	Mean	Std. dev.	Min	Max
sales	773	3.897801	.9168304	1	5
logistic	773	3.847348	.869747	1	5
documentat~n	773	3.941785	.9036342	1	5
packaging	773	4.104787	.8305316	1	5
look	773	4.413972	.7562598	1	5
deployment	773	4.147477	.8057336	1	5
usability	773	4.288486	.8228186	1	5
techsup	773	3.764554	1.00848	1	5
training	773	3.633894	.9931058	1	5
service	773	3.569211	1.035351	1	5
reliability	773	4.26132	.9142039	1	5
information	773	4.003881	.9225081	1	5
communicat~n	773	3.821475	.9746552	1	5
CS	773	2.663648	.5787118	1	3

Customer Status	Freq.	Percent	Cum.
1	43	5.56	5.56
2	174	22.51	28.07
3	556	71.93	100.00
Total	773	100.00	

CS is an ordinal variable measured in a three-point scale (Det, Pas, Pro) and measures the tendency of the respondents to be a detractor, a passively satisfied customer or a promoter, according to their ***willingness to recommend*** the company or its products/services to a colleague or a friend

Correlation Matrix

Limitations of Bivariate Analysis

The correlation matrix is a useful tool for indicating those attributes with the highest correlation with CS (the variable related with NPS), but the tabulated correlation coefficients come from a bivariate analysis and **do not take into account the overall effects of the other attributes**.

The correlation coefficients coming from a bivariate analysis, being limited to the correlation between CS and a single factor, do not describe the complex relationship between all the CX attributes and CS → **lack the ability to view multidimensional relationship** [16].

	sales	logistic	docume~n	packag~g	look	deploy~t	usabil~y	techsup	training	service	reliab~y	inform~n	commun~n	CS
sales	1.0000													
logistic	0.6318	1.0000												
documentat~n	0.3509	0.4221	1.0000											
packaging	0.3849	0.4185	0.5069	1.0000										
look	0.3955	0.3857	0.4087	0.4526	1.0000									
deployment	0.4237	0.4628	0.4228	0.3892	0.5736	1.0000								
usability	0.3688	0.3313	0.4251	0.3822	0.5093	0.5942	1.0000							
techsup	0.5049	0.4891	0.4654	0.3651	0.3301	0.4206	0.4488	1.0000						
training	0.4283	0.4091	0.4150	0.2884	0.2900	0.3541	0.3466	0.6252	1.0000					
service	0.4912	0.4821	0.3913	0.2996	0.2992	0.3635	0.3513	0.6310	0.5481	1.0000				
reliability	0.3704	0.3858	0.4089	0.3750	0.4485	0.4435	0.5265	0.4026	0.3010	0.3928	1.0000			
information	0.3711	0.3947	0.6529	0.4289	0.4879	0.4959	0.5190	0.4813	0.4427	0.4018	0.4780	1.0000		
communicat~n	0.4956	0.4904	0.5103	0.3768	0.4132	0.4806	0.4390	0.5871	0.4891	0.5565	0.4464	0.5943	1.0000	
CS	0.3819	0.3482	0.3192	0.2513	0.3807	0.4093	0.5033	0.3902	0.2813	0.3589	0.5312	0.3979	0.4469	1.0000

ologit – Full Model

. ologit CS sales logistic documentation packaging look deployment usability techsup training service reliability information communication

```
Ordered logistic regression                         Number of obs =    773
                                                    LR chi2(13)   = 337.07
                                                    Prob > chi2   = 0.0000
Log likelihood = -398.37568                         Pseudo R2     = 0.2973
```

CS	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
sales	.2924885	.1375807	2.13	0.034	.0228353	.5621418
logistic	.1998967	.1531482	1.31	0.192	-.1002683	.5000616
documentation	-.0992979	.1458566	-0.68	0.496	-.3851715	.1865757
packaging	-.1884954	.143987	-1.31	0.190	-.4707047	.0937139
look	.1737005	.156352	1.11	0.267	-.1327438	.4801448
deployment	.1888927	.16442	1.15	0.251	-.1333645	.51115
usability	.6872048	.1470216	4.67	0.000	.3990476	.9753619
techsup	.1929921	.1427708	1.35	0.176	-.0868335	.4728178
training	-.1267808	.1351841	-0.94	0.348	-.3917367	.1381752
service	.1311774	.1273799	1.03	0.303	-.1184826	.3808375
reliability	.758207	.1201008	6.31	0.000	.5228137	.9936003
information	.0762149	.1499094	0.51	0.611	-.2176021	.3700319
communication	.4178189	.13459	3.10	0.002	.1540274	.6816104
/cut1	6.919017	.7545663			5.440094	8.397939
/cut2	9.777139	.8162312			8.177355	11.37692

Multicollinearity check

Analysis of the bivariate correlations between the Xs

The correlation matrix shows the bivariate correlations between the independent variables, but **Attention**!
One independent variable may be a linear combination of several independent variables, and yet not be highly correlated with any one of them (Williams, R. A., *Multicollinearity*, Last revised January 13, 2015).

Examining the tolerances or VIFs is probably superior to examining the bivariate correlations

Variable	Obs	Mean	Std. dev.	Min	Max
sales	773	3.897801	.9168304	1	5
logistic	773	3.847348	.869747	1	5
documentat~n	773	3.941785	.9036342	1	5
packaging	773	4.104787	.8305316	1	5
look	773	4.413972	.7562598	1	5
deployment	773	4.147477	.8057336	1	5
usability	773	4.288486	.8228186	1	5
techsup	773	3.764554	1.00848	1	5
training	773	3.633894	.9931058	1	5
service	773	3.569211	1.035351	1	5
reliability	773	4.26132	.9142039	1	5
information	773	4.003881	.9225081	1	5
communicat~n	773	3.821475	.9746552	1	5
CS	773	2.663648	.5787118	1	3

. cor sales logistic documentation packaging look deployment usability techsup training service reliability information communication CS

	sales	logistic	docume~n	packag~g	look	deploy~t	usabil~y	techsup	training	service	reliab~y	inform~n	commun~n	CS
sales	1.0000													
logistic	0.6318	1.0000												
documentat~n	0.3509	0.4221	1.0000											
packaging	0.3849	0.4185	0.5069	1.0000										
look	0.3955	0.3857	0.4087	0.4526	1.0000									
deployment	0.4237	0.4628	0.4228	0.3892	0.5736	1.0000								
usability	0.3688	0.3313	0.4251	0.3822	0.5093	0.5942	1.0000							
techsup	0.5049	0.4891	0.4654	0.3651	0.3301	0.4206	0.4488	1.0000						
training	0.4283	0.4091	0.4150	0.2884	0.2900	0.3541	0.3466	0.6252	1.0000					
service	0.4912	0.4821	0.3913	0.2996	0.2992	0.3635	0.3513	0.6310	0.5481	1.0000				
reliability	0.3704	0.3858	0.4089	0.3750	0.4485	0.4435	0.5265	0.4026	0.3010	0.3928	1.0000			
information	0.3711	0.3947	0.6529	0.4289	0.4879	0.4959	0.5190	0.4813	0.4427	0.4018	0.4780	1.0000		
communicat~n	0.4956	0.4904	0.5103	0.3768	0.4132	0.4806	0.4390	0.5871	0.4891	0.5565	0.4464	0.5943	1.0000	
CS	0.3819	0.3482	0.3192	0.2513	0.3807	0.4093	0.5033	0.3902	0.2813	0.3589	0.5312	0.3979	0.4469	1.0000

Multicollinearity check

Analysis of the multivariate correlations between the Xs - VIF by ***estat vif*** and ***collin***

A commonly given rule of thumb is that VIFs of 10 or higher (or equivalently, tolerances of 0.10 or less) may be reason for concern. This is, however, just a rule of thumb; Allison says he gets concerned when the VIF is over 2.5 and the tolerance is under 0.40.

The Variance Inflation Factor (VIF) results indicate no significant issue of multicollinearity

. ***reg*** CS sales logistic documentation packaging look deployment usability techsup training service reliability information communication
. estat vif

Variable	VIF	1/VIF
techsup	2.40	0.416496
information	2.36	0.422873
communicat~n	2.18	0.458705
documentat~n	2.07	0.482758
deployment	2.04	0.491388
logistic	2.02	0.495907
service	2.01	0.497560
usability	1.98	0.503985
sales	1.97	0.508257
training	1.85	0.541943
look	1.82	0.549569
reliability	1.65	0.604823
packaging	1.58	0.631824
Mean VIF	1.99	

. ***collin*** sales logistic documentation packaging look deployment usability techsup training service reliability information communication

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
sales	1.97	1.40	0.5083	0.4917
logistic	2.02	1.42	0.4959	0.5041
documentation	2.07	1.44	0.4828	0.5172
packaging	1.58	1.26	0.6318	0.3682
look	1.82	1.35	0.5496	0.4504
deployment	2.04	1.43	0.4914	0.5086
Usability	1.98	1.41	0.5040	0.4960
techsup	2.40	1.55	0.4165	0.5835
training	1.85	1.36	0.5419	0.4581
service	2.01	1.42	0.4976	0.5024
Reliability	1.65	1.29	0.6048	0.3952
information	2.36	1.54	0.4229	0.5771
communication	2.18	1.48	0.4587	0.5413
Mean VIF	1.99			

ologit – Model Selection

Backword Elimination by *stepwise* Stata command

```
. stepwise, pr(0.05): ologit CS sales logistic documentation packaging look deployment usability techsup training service reliability information communication
```

```
Wald test, begin with full model:
p = 0.6112 >= 0.0500, removing information
p = 0.6069 >= 0.0500, removing documentation
p = 0.3301 >= 0.0500, removing training
p = 0.3844 >= 0.0500, removing service
p = 0.2689 >= 0.0500, removing look
p = 0.2079 >= 0.0500, removing techsup
p = 0.2238 >= 0.0500, removing packaging
p = 0.1567 >= 0.0500, removing logistic
p = 0.0631 >= 0.0500, removing deployment
```

```
Ordered logistic regression                             Number of obs =    773
                                                        LR chi2(4)    = 325.10
                                                        Prob > chi2   = 0.0000
Log likelihood = -404.36103                             Pseudo R2     = 0.2867
```

CS	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
sales	.4372996	.1201564	3.64	0.000	.2017973	.6728019
reliability	.7944793	.11361	6.99	0.000	.5718078	1.017151
communication	.5584457	.1142727	4.89	0.000	.3344754	.782416
usability	.7832053	.1262855	6.20	0.000	.5356903	1.03072
/cut1	6.448235	.632528			5.208503	7.687967
/cut2	9.29086	.7035583			7.911911	10.66981

ologit – Model Selection

Variable selection by *gvselect* Stata command

. gvselect <term> sales logistic documentation packaging look deployment usability techsup training service reliability information communication: ologit CS <term>

# Preds	LL	AIC	BIC
1	-466.4609	938.9217	952.8726
2	-430.965	869.93	888.5312
3	-411.0886	832.1773	855.4286
4	-404.361	820.7221	848.6237
5	-402.6499	819.2997	851.8517
6	-401.5966	819.1932	856.3954
7	-400.863	819.7259	861.5784
8	-400.1035	820.207	866.7098
9	-399.4905	820.981	872.1341
10	-399.1133	822.2266	878.03
11	-398.6374	823.2748	883.7285
12	-398.5045	825.0091	890.113
13	-398.3757	826.7514	896.5055

The Stata command *gvselect* provides the best combinations of predictors for each level of model complexity [1].
gvselect applies the **leaps-and bounds algorithm** (Furnival and Wilson 1974) which allows to perform variable selection on a wide variety of normal and nonnormal models using information criteria like AIC and BIC.

```
Ordered logistic regression                        Number of obs =    773
                                                   LR chi2(4)    = 325.10
                                                   Prob > chi2   = 0.0000
Log likelihood = -404.36103                        Pseudo R2     = 0.2867
```

CS	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
sales	.4372996	.1201564	3.64	0.000	.2017973	.6728019
usability	.7832053	.1262855	6.20	0.000	.5356903	1.03072
reliability	.7944793	.11361	6.99	0.000	.5718078	1.017151
communication	.5584457	.1142727	4.89	0.000	.3344754	.782416
/cut1	6.448235	.632528			5.208503	7.687967
/cut2	9.29086	.7035583			7.911911	10.66981

[1] Lindsey, C. and Sheather S. 2015. Best subsets variable selection in nonnormal regression models. *Stata Journal* 15: 1046-1059.

Table of Models' coefficients and IC by Stata command *collect*

	M13	M12	M11	M10	M9	M8	M7	M6	M5	M4
Sales	0.292	0.292	0.299	0.294	0.305	0.316	0.340	0.327	0.407	0.437
	(0.034)	(0.034)	(0.029)	(0.031)	(0.025)	(0.020)	(0.011)	(0.014)	(0.001)	(0.000)
Logistic	0.200	0.197	0.192	0.185	0.199	0.205	0.232	0.210		
	(0.192)	(0.198)	(0.208)	(0.225)	(0.188)	(0.174)	(0.121)	(0.157)		
Documentation	-0.099	-0.068								
	(0.496)	(0.607)								
Packaging	-0.188	-0.187	-0.205	-0.205	-0.211	-0.172	-0.163			
	(0.190)	(0.193)	(0.143)	(0.141)	(0.129)	(0.198)	(0.224)			
Look	0.174	0.183	0.178	0.172	0.171					
	(0.267)	(0.238)	(0.249)	(0.266)	(0.269)					
Deployment	0.189	0.193	0.188	0.188	0.191	0.244	0.244	0.231	0.279	
	(0.251)	(0.240)	(0.251)	(0.248)	(0.241)	(0.116)	(0.115)	(0.134)	(0.063)	
Usability	0.687	0.696	0.690	0.681	0.670	0.694	0.721	0.696	0.676	0.783
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TechSup	0.193	0.195	0.189	0.136	0.172	0.155				
	(0.176)	(0.170)	(0.183)	(0.299)	(0.167)	(0.208)				
Training	-0.127	-0.121	-0.130							
	(0.348)	(0.369)	(0.330)							
Service	0.131	0.130	0.133	0.108						
	(0.303)	(0.307)	(0.297)	(0.384)						
Reliability	0.758	0.765	0.761	0.767	0.783	0.792	0.794	0.772	0.792	0.794
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Information	0.076									
	(0.611)									
Communication	0.418	0.432	0.418	0.410	0.437	0.450	0.503	0.500	0.519	0.558
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
cut1	6.919	6.931	6.955	7.028	6.982	6.805	6.797	7.057	6.849	6.448
cut2	9.777	9.789	9.812	9.881	9.835	9.657	9.646	9.905	9.697	9.291
AIC	826.8	825.0	823.3	822.2	821.0	820.2	819.8	819.3	819.3	820.7
BIC	896.5	890.1	883.7	878.0	872.1	866.7	861.6	856.5	851.9	848.6

Specification of Ordinal Independent Variables as continuous variables

In this contest we have **specified all the ordinal independent variables as continuous variables**.
When the model contains several ordinal independent variables, by specifying these variables in the model as continuous, allows to gain a **more parsimonious and so easier to interpret model** [23].
However we can not assume linear effects with ordinal independent variables without performing formal tests to justify treating the ordinal variables as continuous.
According to Williams' indications **two specific hypothesis tests** have been performed in order to justify the specification in the model of the 4 independent variables (CX attributes) as continuous variable [35].

Wald X^2 Test

- for a Wald test, only one model need to be estimated
- both the continuous and the categorical versions of the ordinal variable are included in the model by specifying the categorical term via the use of the o. notation (o stands for omitted)
- after running the model the Stata command *testparm* allows to evaluate if the indicator variables, either individually or as a group (overall test), significantly improve or not the model fit respect to what we obtain by specifying the variable in the model as continuous

Likelihood Ratio X^2 Test

- it compares an unconstrained model, where the 4 independent ordinal variables are specified as categorical (factor variable notation), versus a constrained model, where the 4 variables are specified as continuous
- the LR test assumes that the two models are nested
- after running the two models, the Stata command *lrtest* provides the LR X^2 statistic, and, by the option *stat*, also the IC statistics, which allows to evaluate if the assumption of linear effects is justified
- a non significant LR X^2 statistic (referred to the difference in terms of likelihood between the two models) means that the constrained model has the same fit as the unconstrained one, while the two IC, AIC and BIC, allow to evaluate if the constrained model is to be preferred respect to the unconstrained one (lower values)

Specification of Ordinal Independent Variables as continuous variables

Wald test

. ologit CS sales usability reliability communication o(1 2).sales o(1 2).usability o(1 2).reliability o(1 2).communication

```
Ordered logistic regression                             Number of obs =    773
                                                        LR chi2(16)   = 344.11
                                                        Prob > chi2   = 0.0000
Log likelihood = -394.85689                             Pseudo R2     = 0.3035
```

CS	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
sales	-.6575156	1.014327	-0.65	0.517	-2.64556	1.330529
usability	2.066925	.9856356	2.10	0.036	.1351148	3.998735
reliability	.1427809	.8068625	0.18	0.860	-1.438641	1.724202
communication	1.49585	.6271842	2.39	0.017	.2665916	2.725108
sales						
2	0	(omitted)				
3	.6378574	1.250497	0.51	0.610	-1.813072	3.088787
4	2.08046	2.23249	0.93	0.351	-2.29514	6.456059
5	2.883373	3.239513	0.89	0.373	-3.465955	9.2327
usability						
2	0	(omitted)				
3	-2.324056	1.442419	-1.61	0.107	-5.151145	.5030335
4	-3.549787	2.378349	-1.49	0.136	-8.211265	1.111691
5	-4.6212	3.347802	-1.38	0.167	-11.18277	1.940373
reliability						
2	0	(omitted)				
3	1.546046	1.106852	1.40	0.162	-.6233449	3.715437
4	1.734975	1.870435	0.93	0.354	-1.931009	5.40096
5	2.533489	2.665578	0.95	0.342	-2.690948	7.757926
communication						
2	0	(omitted)				
3	-1.798051	.9166297	-1.96	0.050	-3.594612	-.0014898
4	-2.438505	1.521886	-1.60	0.109	-5.421348	.5443373
5	-3.412763	2.153486	-1.58	0.113	-7.633517	.8079915
/cut1	6.01805	2.625937			.8713085	11.16479
/cut2	8.913529	2.656576			3.706735	14.12032

. testparm i.sales i.usability i.reliability i.communication

```
 ( 1)  [CS]3.sales = 0
 ( 2)  [CS]4.sales = 0
 ( 3)  [CS]5.sales = 0
 ( 4)  [CS]3.usability = 0
 ( 5)  [CS]4.usability = 0
 ( 6)  [CS]5.usability = 0
 ( 7)  [CS]3.reliability = 0
 ( 8)  [CS]4.reliability = 0
 ( 9)  [CS]5.reliability = 0
 (10)  [CS]3.communication = 0
 (11)  [CS]4.communication = 0
 (12)  [CS]5.communication = 0

           chi2( 12) =   18.56
         Prob > chi2 =    0.0997
```

LR test

. lrtest M4 M4factor, stat

```
Likelihood-ratio test
Assumption: M4 nested within M4factor

LR chi2(12) =  19.01
Prob > chi2 = 0.0883

Akaike's information criterion and Bayesian information criterion
```

Model	N	ll(null)	ll(model)	df	AIC	BIC
M4	773	-566.9113	-404.361	6	820.7221	848.6237
M4factor	773	-566.9113	-394.8569	18	825.7138	909.4188

ologit – Restricted Model

$$ln\left[\frac{P(y_i = Det|\boldsymbol{x_i})}{P\left(y_i = Pas\,\&Pro\,\middle|\,\boldsymbol{x_i}\right)}\right] = \tau_1 - \boldsymbol{x}_i\boldsymbol{\beta} = \tau_1 - (\beta_s s_i + \beta_u u_i + \beta_r r_i + \beta_c c_i)$$

$$ln\left[\frac{P\left(y_i = Det\,\&Pas\,\middle|\,\boldsymbol{x_i}\right)}{P\left(y_i = Pro\,\middle|\,\boldsymbol{x_i}\right)}\right] = \tau_2 - \boldsymbol{x}_i\boldsymbol{\beta} = \tau_2 - (\beta_s s_i + \beta_u u_i + \beta_r r_i + \beta_c c_i)$$

. ologit CS sales usability reliability communication

```
Ordered logistic regression                         Number of obs =    773
                                                    LR chi2(4)    = 325.10
                                                    Prob > chi2   = 0.0000
Log likelihood = -404.36103                         Pseudo R2     = 0.2867

------------------------------------------------------------------------------
           CS | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
--------------+---------------------------------------------------------------
        sales |   .4372996   .1201564     3.64   0.000     .2017973    .6728019
    usability |   .7832053   .1262855     6.20   0.000     .5356903     1.03072
  reliability |   .7944793     .11361     6.99   0.000     .5718078    1.017151
communication |   .5584457   .1142727     4.89   0.000     .3344754     .782416
--------------+---------------------------------------------------------------
        /cut1 |   6.448235    .632528                      5.208503    7.687967
        /cut2 |    9.29086   .7035583                      7.911911    10.66981
------------------------------------------------------------------------------
```

Legend	
s	sales
u	usability
r	reliability
c	communication
Det	detractors
Pas	passively satisfied customers
Pro	promoters

Respondents who attribute higher scores to these significant CX attributes tend to assign higher scores to the LTR question, so decreasing the likelihood of bad word-of-mouth (to be Passives rather than Detractors) and increasing the likelihood to recommend the company or its products/services to friends or colleagues (to be Promoters rather than Passives and Detractors).
The effect of usability and reliability on moving the CS to higher levels is greater than the effect shown by sales and communication.

Testing the Parallel Regression Assumption by the Brant test

The Stata command *brant* (this command is part of the SPost suite developed by J. Scott Long & Jeremy Freese [19]) performs a ***Brant test*** of the ***parallel regression assumption*** [8] after the Stata command *ologit*.
The test collapses the categories above and below each cutpoint, then fits a series of binary logistic regressions and compares the slope coefficients of the "*J*-1" binary logits implied by the ordered regression model (the ordinal variable with "*J*" categories is dichotomized, then a set of "*J*-1" binary logits is run).
The *brant* command compares the coefficients jointly and separately, providing both an overall test of whether any variable specified in the model violates the assumption, as well as tests of the parallel-line assumption for each of the independent variable separately [31].

```
. brant, details

Estimated coefficients from binary logit
```

Variable	y_gt_1	y_gt_2
sales	0.634	0.384
	2.59	3.08
usability	0.678	0.807
	3.27	5.55
reliability	1.138	0.652
	5.71	5.31
communicat~n	0.428	0.575
	1.92	4.66
_cons	-7.373	-8.652
	-6.24	-11.23

```
Legend: b/t

Brant test of parallel regression assumption
```

	chi2	p>chi2	df
All	5.97	0.202	4
sales	0.98	0.323	1
usability	0.31	0.577	1
reliability	5.36	0.021	1
communication	0.39	0.530	1

```
A significant test statistic provides evidence that the parallel
regression assumption has been violated.
```

The *detail* option provides a table of coefficients from each of the binary logistic regression.
First, it is category 1 versus categories 2 & 3; then categories 1 & 2 versus 3

If the parallel-line assumption is met, all the coefficients (other than the constants) should be the same across equations (for each logistic regression) except for sampling variability.
The Brant test gives evidence weather the differences between the coefficients of each variable may be attributed just to sampling variability, or if they are too large to be attributed to ologit assumptions' violation [31].

The Brant test for all the 4 variables is not significant (overall Brant test)

A significant test statistic provides evidence that the parallel regression assumption has been violated for the variable *reliability*

The PPOM as alternative method to the POM where the Proportional Odds Assumption is violated

Consideration on the Brant test
According to what suggested by Williams (2006) [31], since multiple variables are being tested (and so multiple tests are being conducted), a more stringent significance α level of 0.01 should be used before deciding that any given variable violates the proportional odds assumption.
It is important to consider that when sample sizes are large, even small violations of the proportional odds assumption can be statistically significant.
More stringent p values could increase the number of variables that meet the parallel lines constraint.
In this specific situation with a significance level of 0.01 the Brant test would not be violated by any of the independent variables specified in the model.
The parallel-lines constraint for reliability would be rejected at the 0.05 level of significance, but not at the 0.01 level of significance, suggesting that we could have confidence in the ologit model.

When the PLA is violated the PPOM represent an alternative model
In practice, however, the parallel-line assumption is often violated. That means that it could be common to find one or more CX attributes that violate the parallel-line assumption, showing not uniform effects across levels of Customer Status.
For this reason, starting from the same data sample, two models have been fitted, the constrained model Ordered Logit Model, also known as Proportional Odds Model (**POM**), and a less constrained model, a special case of the Generalized Ordered Logit Models, also known as Partial Proportional Odds Model (**PPOM**), which allows parameters, where the parallel-line assumption has been violated, to vary across the level of outcomes while others are constrained to be equal.
In this case the parallel-lines assumption was relaxed just for the variable *reliability*.

A step by step comparison between the two models has been done and graphical methods for presenting and interpreting results have been proposed for both models.

gologit2 – user written command for Stata

gologit2 is a Stata ***user-written*** command, which has been released by Richard Williams [31,33], that fits generalized ordered logit models for ordinal dependent variables.
gologit2 is inspired by Vincent Fu's ***gologit*** (1) routine [12] and is backward compatible with it but it provides several additional powerful options.

A major strength of *gologit2* is that it can fit three special cases of the generalized model: the proportional odds/parallel-lines model, the partial proportional odds model, and the logistic regression model.

gologit2 allows to fit **models less restrictive** than ***ologit*** (which fits the Proportional Odds Model), by selectively relaxing the parallel-lines assumption, **but more parsimonious and interpretable** than those fitted by ***mlogit***, which provides models for nominal outcomes as the multinomial logit model.
The *autofit* option greatly simplifies the process of identifying partial proportional odds models that fit the data, whereas the *pl* (parallel lines) and *npl* (nonparallel lines) options can be used when users want greater control over the final model specification.

gologit2

- **GOLM**
  - unconstrained GOLM (same as the original gologit, where no variables need to meet the Proportional Odds Assumption)
- **PPOM**
  - GOLM where some but not all variables meet the Proportional Odds Assumption
- **POM**
  - GOLM where all variables meet the Proportional Odds Assumption (same as ologit)
- **LRM**
  - special case where Y has 2 categories

(1) *gologit* allows to fit just unconstrained generalized ordered logit models

gologit2 – Major strengths

item	Major strengths of *gologit2* [31,33]
1	A key enhancement of *gologit2* is that it allows some of the beta coefficients to be the same for all values of *j*, while others can differ, i.e. it can estimate partial proportional odds models
2	*gologit2* can estimate models that are less restrictive than *ologit* (whose assumptions are often violated), and more parsimonious than non-ordinal alternatives, such as *mlogit* (1)
3	*gologit2* is backward compatible with Vincent Fu's original *gologit* program, but offers many more features
4	A major update now allows *gologit2* to support factor variables notation and the svy:prefix, as well as more of the display options that have been added to Stata in recent years
5	The *predict* command can easily compute predicted probabilities
7	*gologit2* now works correctly with the *margins* command and with Long & Freese's Spost13 commands
7	The *autofit* option allows to relax the parallel-line constraint only for those variables where the assumption is violated, by an iterative process which allows to identify the PPOM that best fits the data, but special options are also available for a greater control over the final model

(1) *gologit2* allows to fit models with less parameters than those fitted by *mlogit* or *gologit*, for which the increased number of parameters can cause some effects to become statistically insignificant [31]

gologit2 – Considerations on the PPOM

item	R. Williams' considerations/suggestions when implementing the gologit/PPOM [31,33]
1	The gologit model or PPOM works best when relatively **few of the variables in the model violate the proportional odds assumption**. If several variables violate the assumption, then the gologit model offers little in the way of parsimony and more widely known techniques such as multinomial logit may be superior
2	The gologit model or PPOM **can produce negative predicted probabilities** [19,20,33]. As referred by Williams [33], such problems are apparently rare, but where the problem does occur, he suggests to combine the categories of the response variable (especially in those cases where the number of occurrences for some categories is small) and/or to simplify the model. Williams also recommends more stringent p values [31] since multiple tests are being conducted. This could increase the number of variables that meet the parallel lines constraint. If the number of negative predicted probabilities is still non-trivial, he suggests to adopt a different statistical tool
3	When **sample sizes are large**, even **small violations** of the proportional odds assumption can be **statistically significant**. The researchers may wish to assess whether the deviations from proportionality are substantively important enough to warrant moving away from the more parsimonious ordered logit model
4	The *gologit2* routine in Stata uses a stepwise procedure called ***autofit*** to identify variables where proportionality constraints should be relaxed. Like all empirical stepwise procedures, caution should be used to avoid **capitalizing on chance**, i.e., just by chance alone some variables may appear to violate the parallel-lines assumption when in reality they do not [31], so **more stringent p values** can be used or the sample can be divided into two parts to see whether results are consistent across the subsamples [33]
5	When the Parallel-Line Assumption (PLA) is violated, **before moving form the POM**, it would be advisable to **check for model misspecification** (important variable could be omitted, or polynomial or squared terms should be included in the model)

gologit2

```
. gologit2 CS sales usability reliability communication, autofit store(gologit)
```

By selecting the option *autofit*, *gologit2* performs a stepwise procedure that relaxes the parallel-lines assumption just for those predictors which violate it (in this case the variable reliability). The ***gologit2*** allows selectively relaxing the assumptions (**PPOM**).

```
------------------------------------------------------------------------------
Testing parallel lines assumption using the .05 level of significance...

Step  1:  Constraints for parallel lines imposed for usability (P Value = 0.9433)
Step  2:  Constraints for parallel lines imposed for communication (P Value = 0.5900)
Step  3:  Constraints for parallel lines imposed for sales (P Value = 0.0949)
Step  4:  Constraints for parallel lines are not imposed for
          reliability (P Value = 0.00617)

Wald test of parallel lines assumption for the final model:

 ( 1)  [1]usability - [2]usability = 0
 ( 2)  [1]communication - [2]communication = 0
 ( 3)  [1]sales - [2]sales = 0

           chi2(  3) =    3.11
         Prob > chi2 =    0.3754
```

The *autofit* option performs a stepwise procedure that starts fitting the totally unconstrained model (backward stepwise selection procedure). Then it does a series of Wald tests for testing whether the variables meet the Parallel-Line Assumption (PLA). The variable with the least significant value on the Wald test is constrained to have the same beta in all the equations. Then the model is refitted constraining that variable. The process goes on until there are no more variables that meet the PLA.
Finally *gologit2* performs an overall Wald test to assess whether the final PPOM violates the PLA, by comparing the PPOM with the original unconstrained model.
A statistically insignificant test value indicates that the final model does not violate the PLA.

```
Generalized Ordered Logit Estimates                 Number of obs =     773
                                                    LR chi2(5)    =  332.85
                                                    Prob > chi2   =  0.0000
Log likelihood = -400.48698                         Pseudo R2     =  0.2936

 ( 1)  [1]usability - [2]usability = 0
 ( 2)  [1]communication - [2]communication = 0
 ( 3)  [1]sales - [2]sales = 0
```

CS	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
1						
sales	.4509033	.1200151	3.76	0.000	.215678	.6861286
usability	.7939583	.1276659	6.22	0.000	.5437378	1.044179
reliability	1.215408	.1975138	6.15	0.000	.8282879	1.602528
communication	.5583723	.1146803	4.87	0.000	.3336031	.7831415
_cons	-7.827135	.829606	-9.43	0.000	-9.453133	-6.201138
2						
sales	.4509033	.1200151	3.76	0.000	.215678	.6861286
usability	.7939583	.1276659	6.22	0.000	.5437378	1.044179
reliability	.6400683	.122293	5.23	0.000	.4003785	.8797581
communication	.5583723	.1146803	4.87	0.000	.3336031	.7831415
_cons	-8.737108	.7185118	-12.16	0.000	-10.14537	-7.328851

gologit2

```
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                                                    Prob > chi2   = 0.0000
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 ( 2)  [1]communication - [2]communication = 0
 ( 3)  [1]sales - [2]sales = 0
```

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Legend	
s	sales
u	usability
r	reliability
c	communication
Det	detractors
Pas	passively satisfied customers
Pro	promoters

$$ln\left[\frac{P(y_i = Pas\,\&Pro|\boldsymbol{x_i})}{P(y_i = Det\,|\,\boldsymbol{x_i})}\right] = \alpha_1 + \boldsymbol{x}_i\boldsymbol{\beta}_1 = \alpha_1 + \beta_s s_i + \beta_u u_i + \boxed{\beta_{r1}} r_i + \beta_c c_i$$

$$ln\left[\frac{P(y_i = Pro\,|\,\boldsymbol{x_i})}{P(y_i = Det\,\&Pas\,|\,\boldsymbol{x_i})}\right] = \alpha_2 + \boldsymbol{x}_i\boldsymbol{\beta}_2 = \alpha_2 + \beta_s s_i + \beta_u u_i + \boxed{\beta_{r2}} r_i + \beta_c c_i$$

gologit2 vs *ologit* – LR test and information criteria (AIC and BIC)

```
. estimates stats ologit gologit

Akaike's information criterion and Bayesian information criterion
```

Model	N	ll(null)	ll(model)	df	AIC	BIC
ologit	773	-566.9113	-404.361	6	820.7221	848.6237
gologit	773	-566.9113	-400.487	7	814.974	847.5259

```
. quietly ologit CS sales usability reliability communication

. quietly fitstat, save

. quietly gologit2 CS sales usability reliability communication, autofit

. fitstat, diff
```

According to Raftery's guidelines an absolute difference in BIC between 0 and 2 provides a weak support for the gologit model vs the ologit model

```
. fitstat, diff
```

	gologit Current	ologit Saved	Difference
Log-likelihood			
Model	-400.487	-404.361	3.874
Intercept-only	-566.911	-566.911	0.000
Chi-square			
D(df=766/767/-1)	800.974	808.722	-7.748
LR(df=5/4/1)	332.849	325.101	7.748
p-value	0.000	0.000	.
R2			
McFadden	0.294	0.287	0.007
McFadden(adjusted)	0.281	0.276	0.005
Cox-Snell/ML	0.350	0.343	0.007
Cragg-Uhler/Nagelkerke	0.455	0.446	0.009
Count	0.780	0.774	0.006
Count(adjusted)	0.217	0.194	0.023
IC			
AIC	814.974	820.722	-5.748
AIC divided by N	1.054	1.062	-0.007
BIC(df=7/6/1)	847.526	848.624	-1.098

```
Difference of    1.098 in BIC provides weak support for current model.
```

gologit2 vs *ologit* – tables of coefficients

gologit2

CS	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
1						
sales	.4509033	.1200151	3.76	0.000	.215678	.6861286
usability	.7939583	.1276659	6.22	0.000	.5437378	1.044179
reliability	1.215408	.1975138	6.15	0.000	.8282879	1.602528
communication	.5583723	.1146803	4.87	0.000	.3336031	.7831415
_cons	-7.827135	.829606	-9.43	0.000	-9.453133	-6.201138
2						
sales	.4509033	.1200151	3.76	0.000	.215678	.6861286
usability	.7939583	.1276659	6.22	0.000	.5437378	1.044179
reliability	.6400683	.122293	5.23	0.000	.4003785	.8797581
communication	.5583723	.1146803	4.87	0.000	.3336031	.7831415
_cons	-8.737108	.7185118	-12.16	0.000	-10.14537	-7.328851

ologit

CS	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
sales	.4372996	.1201564	3.64	0.000	.2017973	.6728019
usability	.7832053	.1262855	6.20	0.000	.5356903	1.03072
reliability	.7944793	.11361	6.99	0.000	.5718078	1.017151
communication	.5584457	.1142727	4.89	0.000	.3344754	.782416
/cut1	6.448235	.632528			5.208503	7.687967
/cut2	9.29086	.7035583			7.911911	10.66981

The **PPOM**, fitted by ***gologit2***, gives evidence that *reliability* has a not uniform effect on moving customers to a higher level of CS.
The effect of reliability on moving customers out of the pool of detractors is almost two times greater than the effect on moving customers inside the pool of promoters, showing a ***decreasing ability of this facet of product/service on improving CS***.

Good performance on *reliability* can ***prevent customers from spreading bad word-of-mouth*** to their friends and colleagues.

Table of coefficients by the Stata command *collect*

- comparison between the POM and the PPOM

As pointed out by Williams [33] even if more parsimonious than the Multinomial Logit Model fitted by *mlogit*, the report generated by *gologit2* for the **PPOM** is still a little hard to read and to understand.

In order to compare the results provided by fitting the **POM** by *ologit*, with those provided by fitting the **PPOM** by g*ologit2* the following tables have been built by the Stata command *collect*.

Table 2

	POM	PPOM	1	2
Sales	0.437		0.451	0.451
	(0.000)		(0.000)	(0.000)
Usability	0.783		0.794	0.794
	(0.000)		(0.000)	(0.000)
Reliability	0.794		1.215	0.640
	(0.000)		(0.000)	(0.000)
Communication	0.558		0.558	0.558
	(0.000)		(0.000)	(0.000)
cut1	6.448			
cut2	9.291			
Intercept			-7.827	-8.737
			(0.000)	(0.000)
AIC	820.7	815.0		
BIC	848.6	847.5		

Table 1

	POM p-value	POM Coefficient	PPOM 1 p-value	PPOM 1 Coefficient	PPOM 2 p-value	PPOM 2 Coefficient
Sales	0.000	0.437	0.000	0.451	0.000	0.451
Usability	0.000	0.783	0.000	0.794	0.000	0.794
Reliability	0.000	0.794	0.000	1.215	0.000	0.640
Communication	0.000	0.558	0.000	0.558	0.000	0.558
cut1		6.448				
cut2		9.291				
Intercept			0.000	-7.827	0.000	-8.737

Interpretation of the PPOM in terms of Odds Ratios

In this study the use of the PPOM has been proposed as an alternative to the POM, because of the violation of the Proportional Odds Assumption (POA) for one independent variable (***reliability***).
For this predictor the Odds Ratios (OR) are not the same across the logits.
The PPOM allows relaxing the POA just for this variable, showing **a greater effect of reliability on moving respondents out of the pool of detractors** (Det) **than on moving respondents into the pool of promoters** (Pro).
If the POM were used instead, the effect of reliability on moving respondents out of the pool of detractors would be underestimated, while the effect on moving respondents into the pool of promoters would be overestimated. This way by ignoring the POA violation **we could fail to accurately reflect the nature of the effect of reliability**.

The Odds Ratio for reliability in logit 1 (***OR***$_1$) shows that for a unit increase in *reliability* respondents are ***3.4 times*** as likely to belong to one of the higher categories ⇨ to be Pas or Pro, as they are to belong to the lowest category ⇨ to be Det, holding the other Xs constant (the factor change in the odds of being a promoter or a passively satisfied customer than being a detractor is ***3.4***).

	POM			PPOM					
				1			2		
	Odds Ratio	95% CI		Odds Ratio	95% CI		Odds Ratio	95% CI	
Sales	1.55	1.22	1.96	1.57	1.24	1.99	1.57	1.24	1.99
Usability	2.19	1.71	2.80	2.21	1.72	2.84	2.21	1.72	2.84
Reliability	2.21	1.77	2.77	3.37	2.29	4.97	1.90	1.49	2.41
Communication	1.75	1.40	2.19	1.75	1.40	2.19	1.75	1.40	2.19

The Odds Ratio for reliability in logit 2 (***OR***$_2$) shows that for a unit increase in *reliability* respondents are ***1.9 times*** as likely to belong to the highest category ⇨ to be Pro, as they are to belong to one of the lower categories ⇨ to be Det or Pas, holding the other Xs constant (the factor change in the odds of being a promoter than being a detractor or a passively satisfied customer is ***1.9***).

As default *gologit2* computes odds ratios of exceeding category *j* → the odds of being in a higher CS than being in a lower CS

Model Interpretation in terms of probability

Model interpretation by ***margins***

Models for multiple outcome as Ordinal Logit Models and Multinomial Logit Models are hard to interpret.
Methods of interpretation using marginal effects for nonlinear models are provided by the Stata command *margins*, which allows to compute Adjusted Predictions and Marginal Effects [19].
The Stata command ***margins*** is a postestimation command that can be run after multiple outcome regression models' commands as *ologit*, *oprobit*, *mlogit*, *gologit2*.

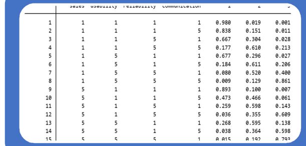
Margins provides three different types of Marginal Effects (three different approaches of computation), which depends on the different ways of controlling for the other variables in the model while computing Adjusted Predictions:

- Average Marginal Effects (**AMEs**) are computed as difference between two Average Adjusted Predictions (**AAPs**)
- Marginal Effects at Means (**MEMs**) are computed as difference between two Adjusted Predictions at Means (**APMs**)
- Marginal Effects at Representative values (**MERs**) are computed as difference between two Adjusted Predictions at specific values of the other variables (**APRs**)

As referred by Long and Freese [19], and by Williams [32,33], both the models, the POM and the PPOM, can be interpreted in terms of Adjusted Predictions and Marginal Effects at interesting pattern of covariates.
The results can be presented by ***tables*** or ***graphs***.

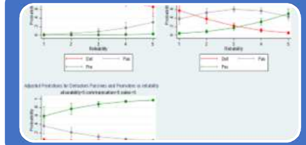
Tables and graphical tools by Stata

In order to present the effects of the 4 significant drivers on driving the probability to be detractor, passively satisfied customer or promoter, the following tools have been developed by Stata.

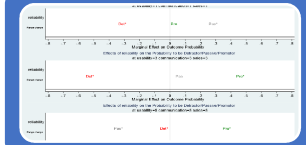


	sales	usability	reliability	communication	1	2	3
1	1	1	1	1	0.980	0.019	0.001
2	1	1	1	5	0.838	0.151	0.011
3	1	1	5	1	0.667	0.304	0.028
4	1	1	5	5	0.177	0.610	0.213
5	1	5	1	1	0.677	0.296	0.027
6	1	5	1	5	0.184	0.611	0.206
7	1	5	5	1	0.080	0.520	0.400
8	1	5	5	5	0.009	0.129	0.861
9	5	1	1	1	0.893	0.100	0.007
10	5	1	1	5	0.473	0.466	0.061
11	5	1	5	1	0.259	0.598	0.143
12	5	1	5	5	0.036	0.355	0.609
13	5	5	1	1	0.268	0.595	0.138
14	5	5	1	5	0.038	0.364	0.598
15	5	5	5	1	0.015	0.192	0.793

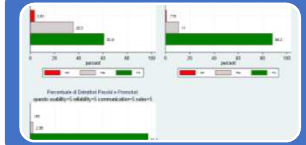
Tables of Adjusted Predictions at specified covariate patterns



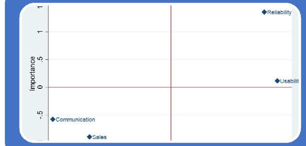
Plots of Adjusted Predictions at specified covariate patterns



Plots of Marginal Effects at specified covariate patterns



Bar Charts of Adjusted Predictions at specified covariate patterns



Importance vs Performance Analysis matrix

Tables of Adjusted Predictions at specified covariate patterns

Probability to be Detractor, Passive or Promoter at specified covariate patterns by ***mtable*** after running ***gologit2***

The effects of the four CX attributes have been estimated in terms of probability at 16 different covariate patterns.

Predicted Probabilities can be suitably tabulated by the SPost command mtable [19], which allows to compare Adjusted Predictions of outcomes under different scenarios.

The Spost13 command *mtable* has been used to tabulate the probabilities to be Detractor (1), Passively Satisfied Customer (2) or Promoter (3), setting the four CX attributes (*sales*, *usability*, *reliability* and *communication*) at the two extreme values (1 = Extremely Unsatisfied and 5 = Very Satisfied).

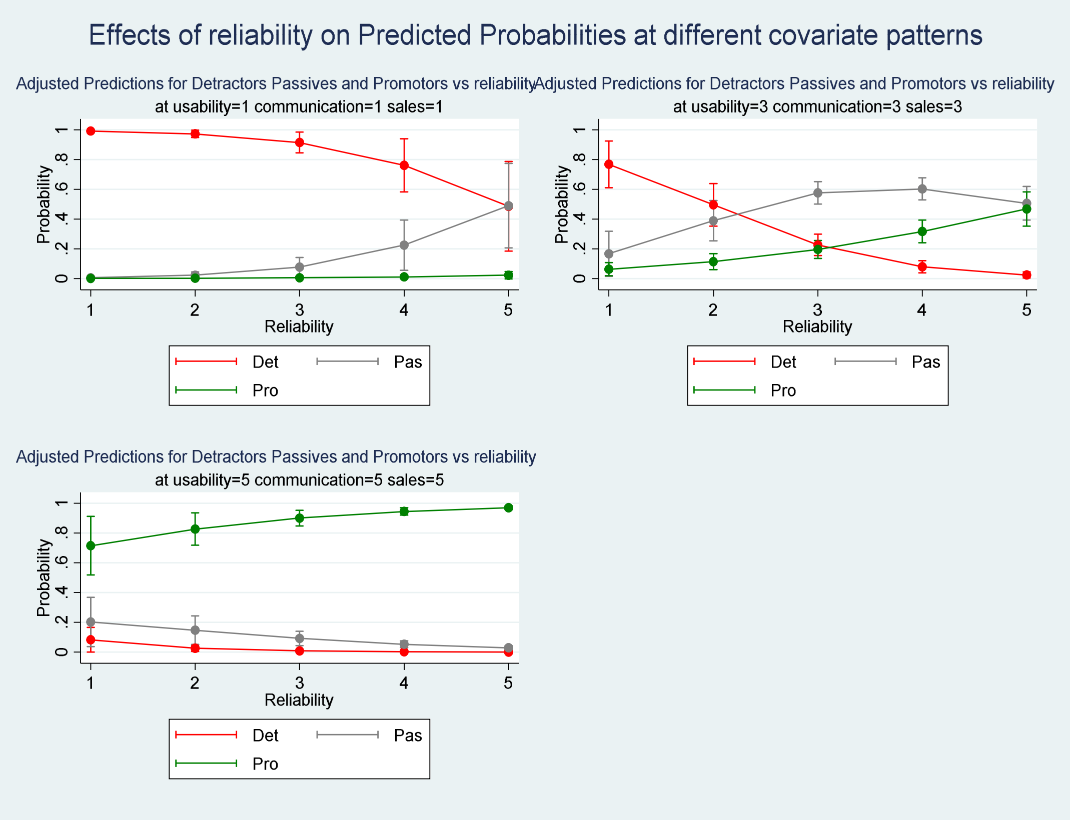
```
. mtable, at(reliability=(1 5) usability=(1 5) communication=(1 5) sales=(1 5))
```

	sales	usability	reliability	communication	1	2	3
1	1	1	1	1	0.992	0.006	0.002
2	1	1	1	5	0.929	0.054	0.017
3	1	1	5	1	0.487	0.490	0.023
4	1	1	5	5	0.092	0.725	0.182
5	1	5	1	1	0.837	0.121	0.042
6	1	5	1	5	0.354	0.354	0.292
7	1	5	5	1	0.038	0.598	0.364
8	1	5	5	5	0.004	0.153	0.842
9	5	1	1	1	0.953	0.036	0.011
10	5	1	1	5	0.684	0.221	0.095
11	5	1	5	1	0.135	0.738	0.127
12	5	1	5	5	0.016	0.408	0.575
13	5	5	1	1	0.457	0.331	0.212
14	5	5	1	5	0.083	0.202	0.715
15	5	5	5	1	0.006	0.217	0.777
16	5	5	5	5	0.001	0.029	0.970

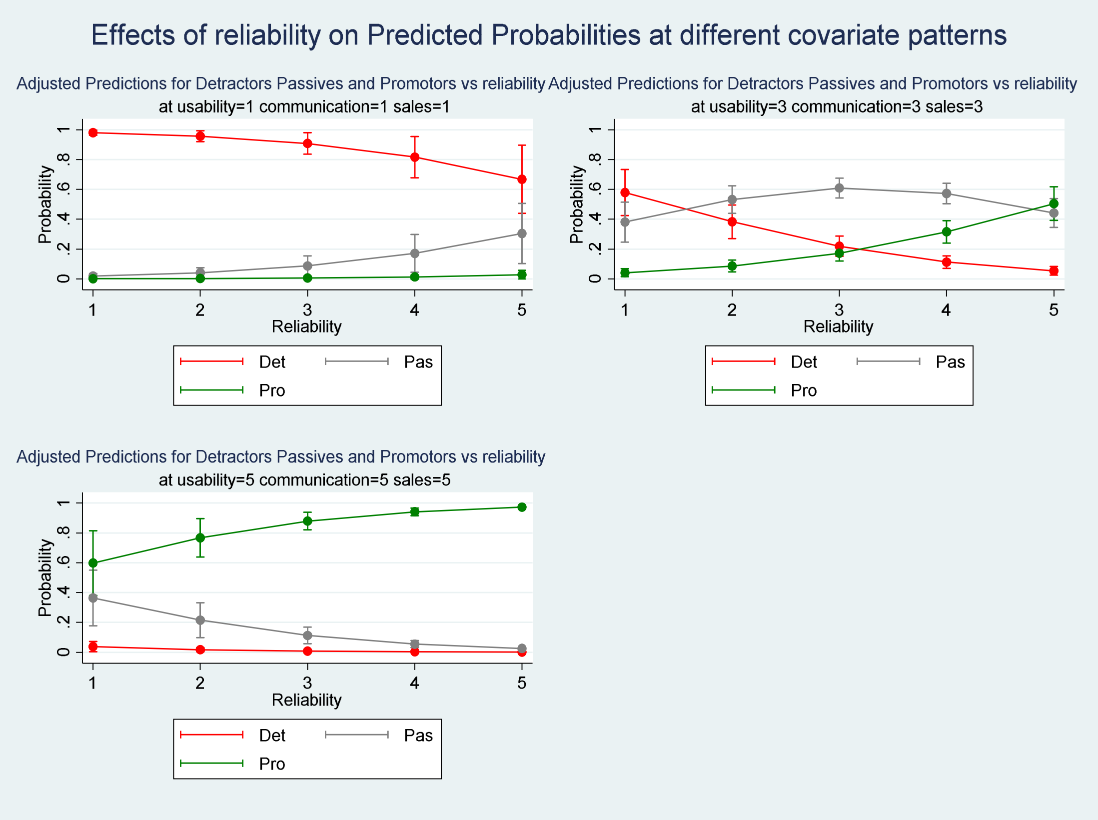
Plots of Adjusted Predictions at specified covariate patterns

Effects of reliability on the Probability to be Detractor, Passive or Promoter by ***margins*** and ***marginsplot***

gologit2



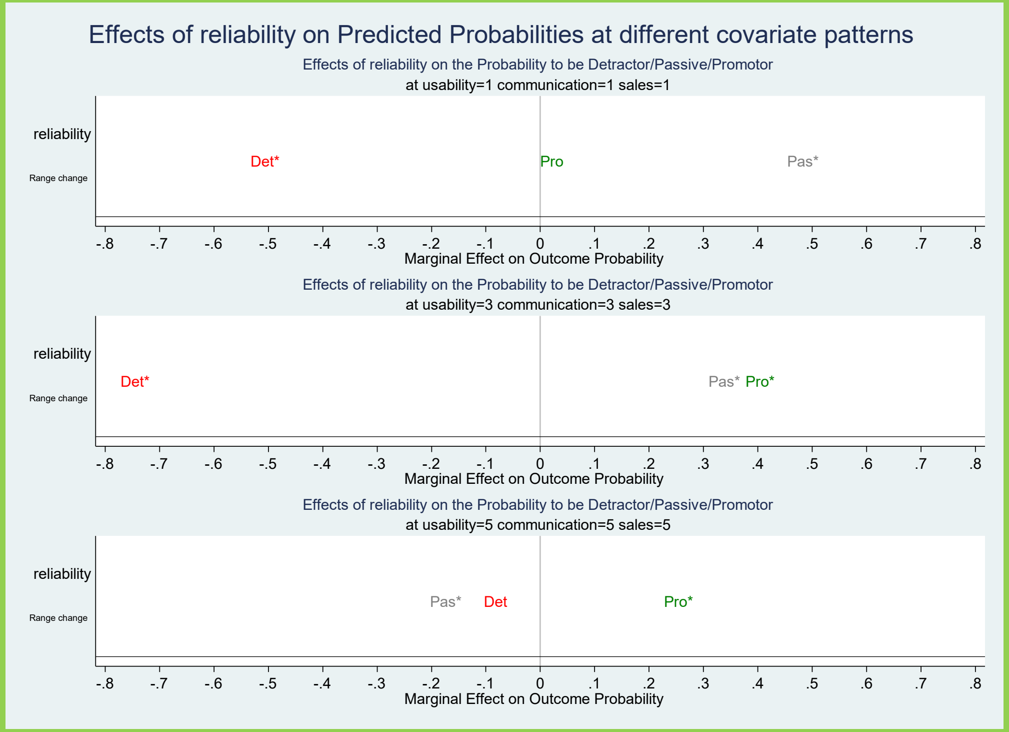
ologit



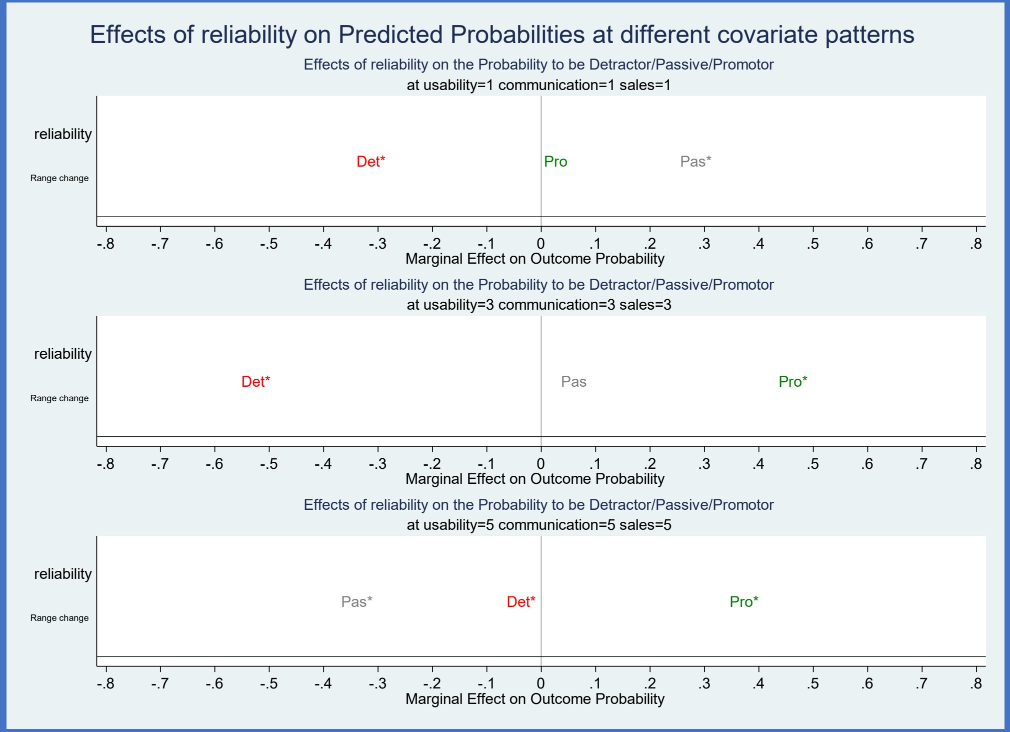
Plots of Marginal Effects at specified covariate patterns

Effects of reliability on the Probability to be Detractor, Passive or Promoter by ***mchange*** and ***mchangeplot***

gologit2



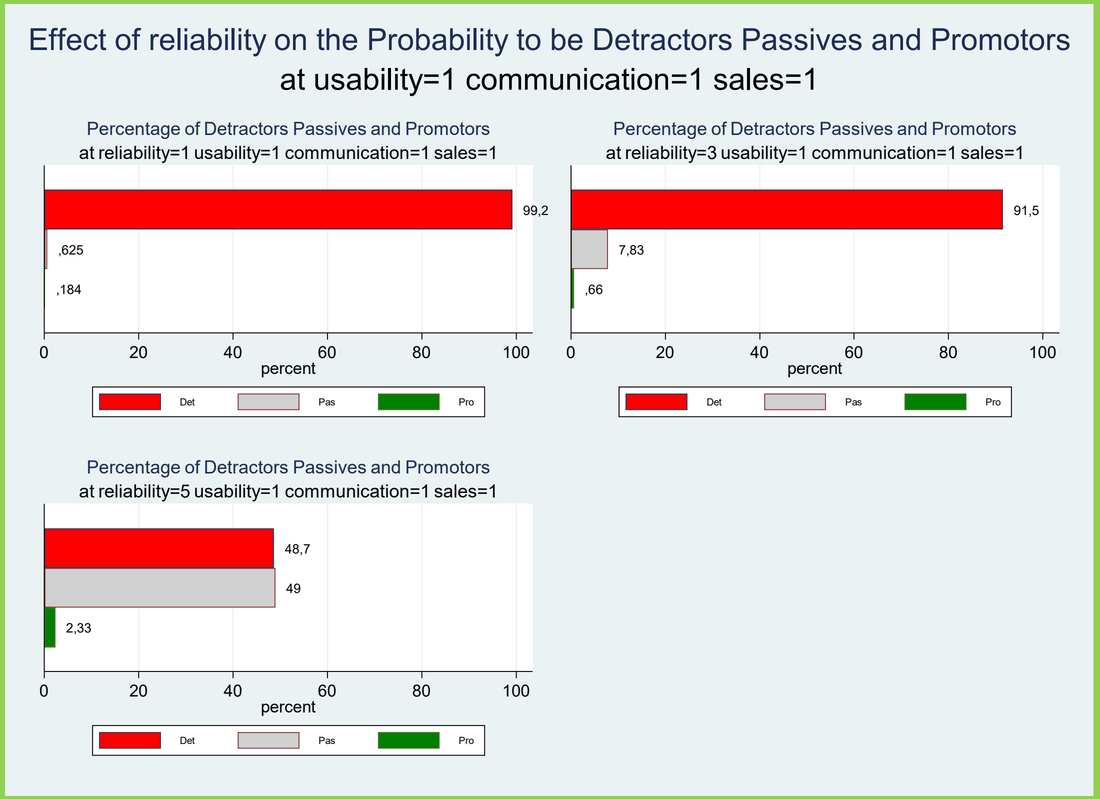
ologit



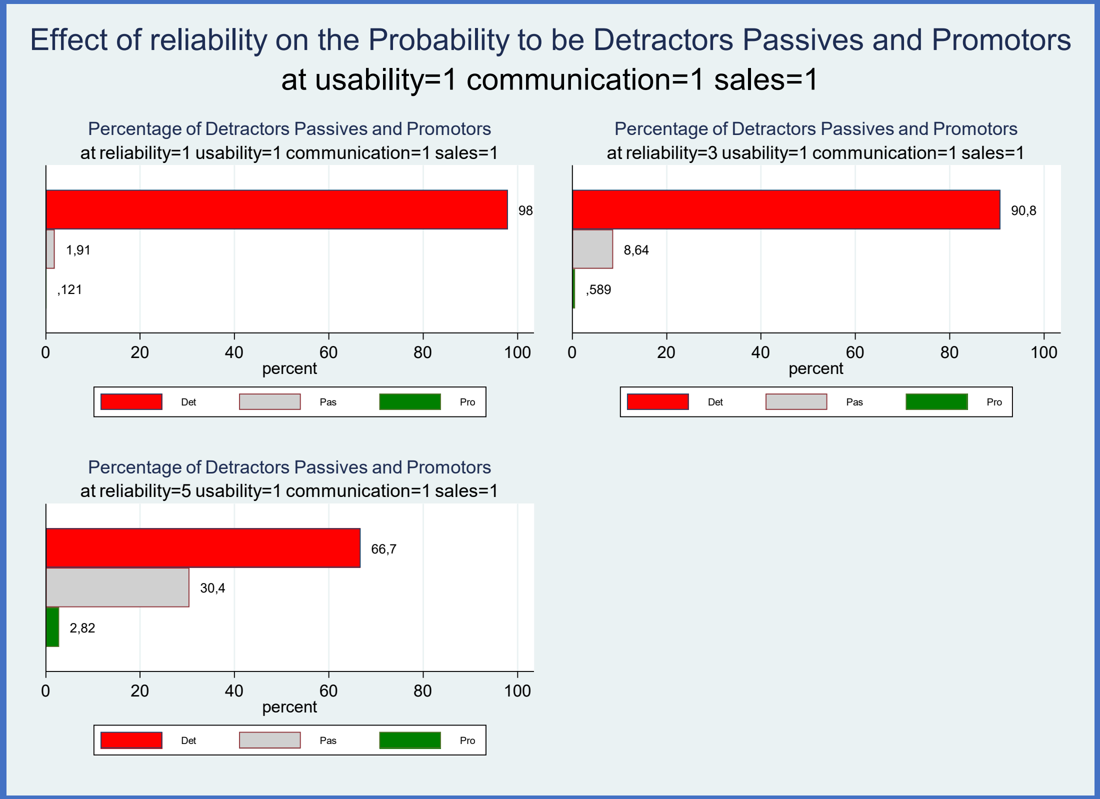
Bar Charts of Adjusted Predictions at specified covariate patterns

Effects of reliability on the Probability to be Detractor, Passive or Promoter at specified covariate patterns

gologit2



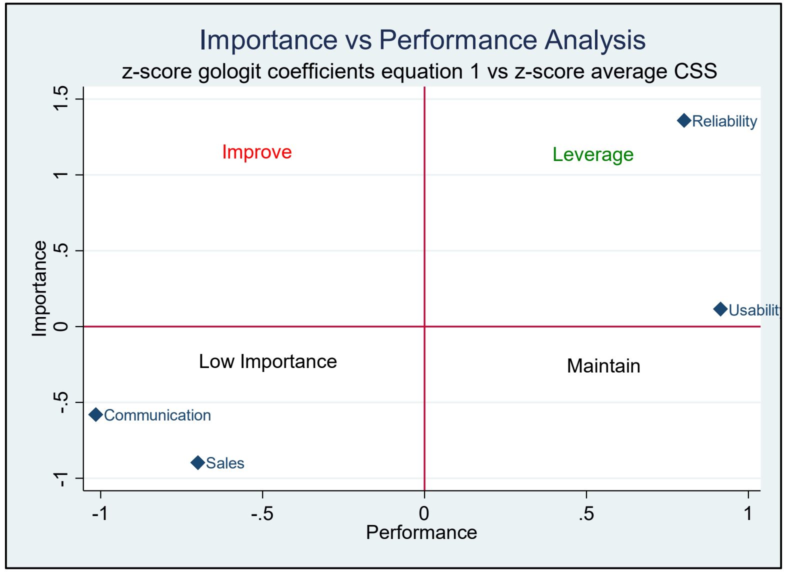
ologit



Key Driver Analysis Reports

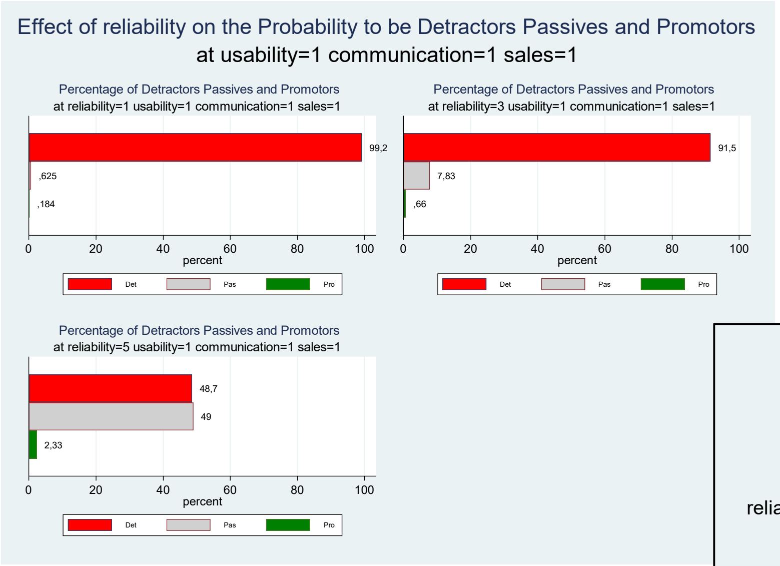
The following graphs have been generated starting from the results provided by fitting the **PPOM** by ***gologit2***

Importance vs Performance Analysis



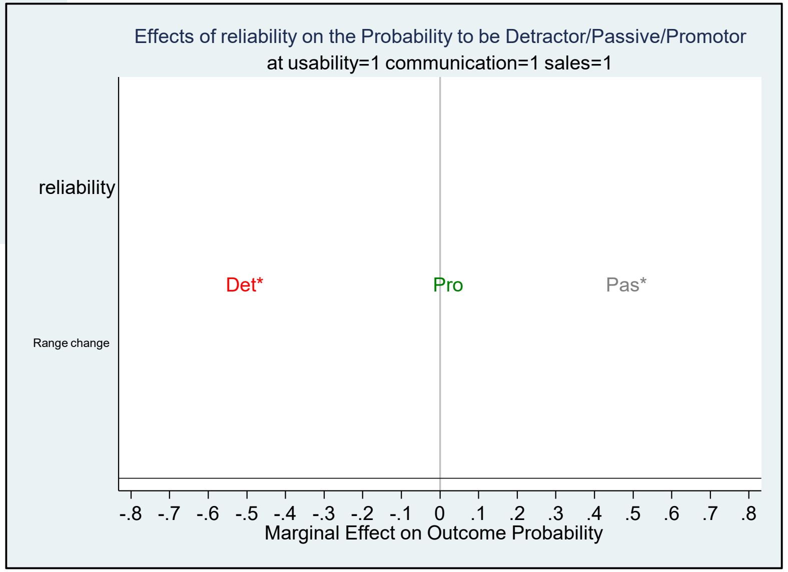
This chart is a scatterplot where the significant drivers brake down in one of the four quadrat.
The graph allows to identify and prioritize which drivers need to be improved.

Bar charts of Adjusted Predictions



Adjusted Predictions at Representative values of the other variables (**APRs**)

Plot of Marginal Effects

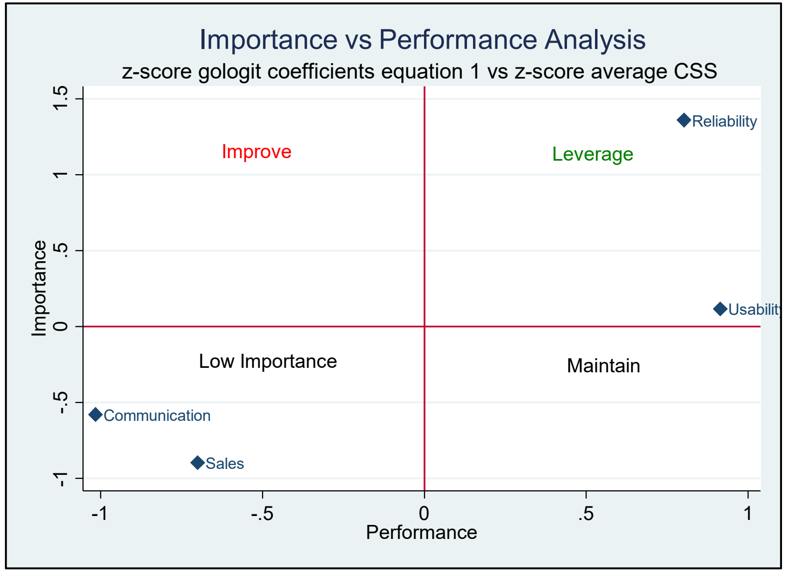


Marginal Effects at Representative values of the other variables (**MERs**)

Importance vs Performance Analysis

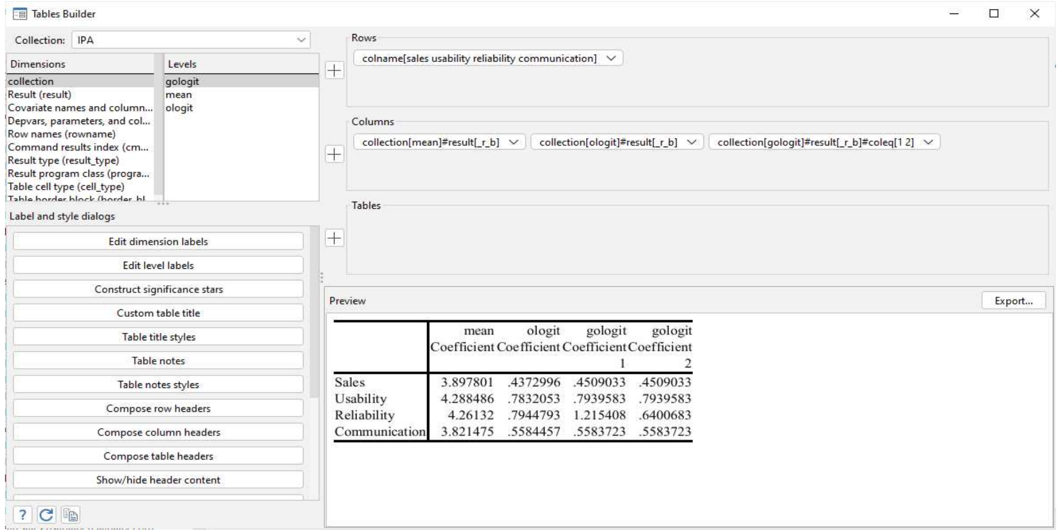
The Net Promoter Score Key Drivers' Analysis (***NPS KDA***) is typically based on statistical regression models which consider NPS as the dependent variable and the Customer Satisfaction Scores on the Customer Experience (CX) attributes as the independent variables [21]. A representation which is commonly used for business decision making is the ***Importance-Performance Analysis*** (IPA), a matrix which allows to identify areas where the company should focus, reduce or maintain its efforts, highlighting the performance and, at the same time, the impact of each item [11,17,21,24]. The matrix represents a useful tool for driving managers on designing appropriate improvement strategies.

In this contest on the x-axis "*Performance*" there is the Z-score of the average Customer Satisfaction Score (CSS) attributed to each of the significant CX attributes, while on the y-axis "*Importance*" there is the Z-score of the regression coefficients provided for ologit or gologit.



Importance vs Performance Analysis

In order to create the IPA graph in Stata with the standardized variables (Z-scores of regression coefficients for ologit or gologit vs Z-scores of the average Customer Satisfaction Score (CSS) attributed to each of the significant CX attributes), the estimation results form *ologit*, *gologit2* and *mean* have been tabulated by the Stata command *collect*, then, they have been imported into an excel sheet to create the variables for generating the matrix in Stata as follows:



	mean Coefficient	ologit Coefficient	gologit Coefficient 1	gologit Coefficient 2
Sales	3.897801	.4372996	.4509033	.4509033
Usability	4.288486	.7832053	.7939583	.7939583
Reliability	4.26132	.7944793	1.215408	.6400683
Communication	3.821475	.5584457	.5583723	.5583723

drivers	mean	ologit	gologit1	gologit2
Sales	3,8978008	0,4372996	0,4509033	0,4509033
Usability	4,2884864	0,7832053	0,7939583	0,7939583
Reliability	4,2613195	0,7944793	1,2154078	0,6400683
Communi	3,8214748	0,5584457	0,5583723	0,5583723

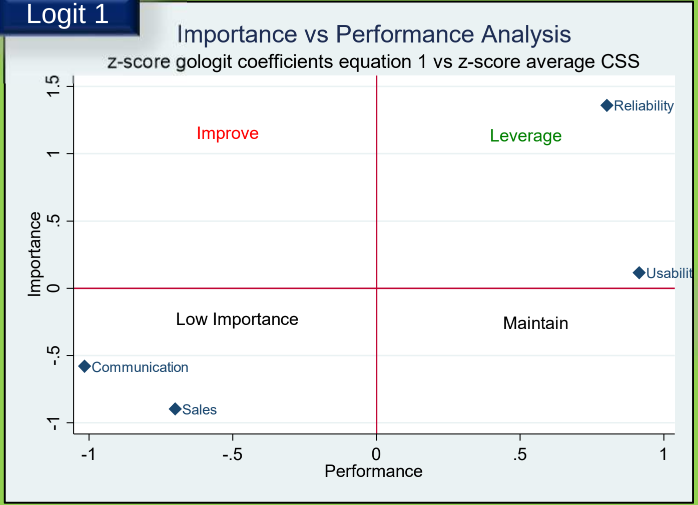
drivers	mean	ologit	gologit1	gologit2	zmean	zologit	zgologit1	zgologit2
Sales	3.8978008	.43729961	.45090331	.45090331	-.7002178	-1.176257	-.8962117	-1.106036
Usability	4.2884864	.78320529	.79395834	.79395834	.9140248	.7983051	.1159454	1.266562
Reliability	4.2613195	.79447927	1.2154078	.64006832	.8017761	.8626613	1.359399	.2022453
Communication	3.8214748	.55844571	.55837232	.55837232	-1.015583	-.484709	-.5791329	-.3627711

Importance vs Performance Analysis

Z-Score coefficients vs Z-score Mean

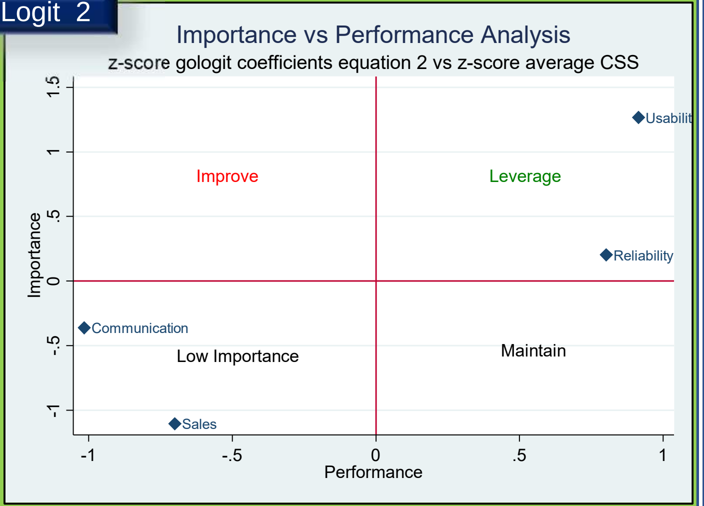
gologit2

Logit 1



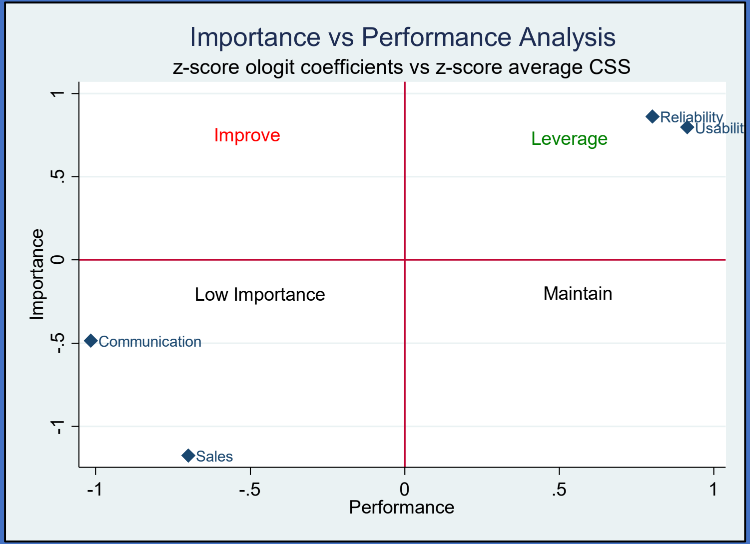
Improvement on reliability has a higher effect on reducing bad word-of-mouth, than on increasing good word-of-mouth.

Logit 2



The gologit, respect to ologit, gives evidence that line managers who are concerned about shrinking the pool of detractors should improve all the four significant CX attributes, especially **focusing on reliability**, while the line managers who are concerned about converting customers into promoters should **focus on usability**.

ologit



Bar charts of Adjusted Predictions by ***mgen***

The effects of the Customer Experience attribute "***reliability***" on CS have been estimated in terms of probability at three different covariate patterns.
The Spost13 command *mgen* has been used to create a variable for the probability of Promoters, Passively Satisfied Customers and Detractors when reliability assumes the values 1, 3, 5 (where 1 = extremely unsatisfied, 3 = neutral and 5 very satisfied) at three different prefixed values of the other three Customer Experience attributes (*usability*, *communication* and *sales*).

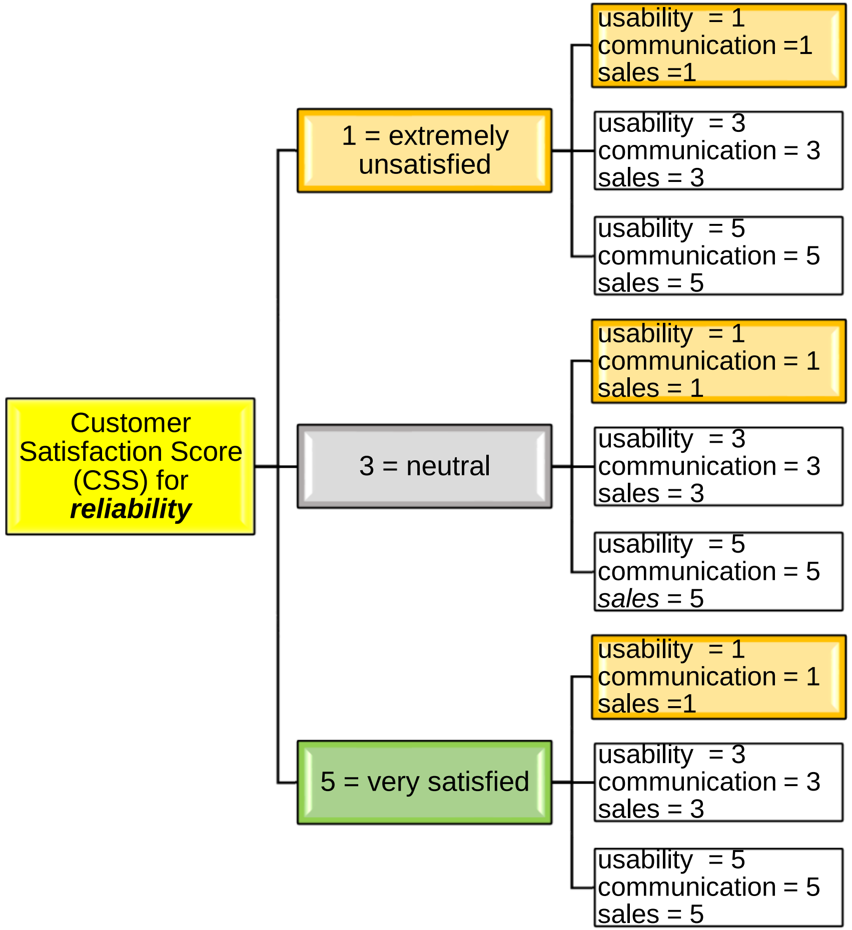
```
. mgen, at (reliability=(1(1)5) usability=1 communication=1 sales=1) stub(R111) replace
```

Than three graphs (***bar charts***) have been created in order to show the estimated percentage of Promoters, Passively Satisfied Customers and Detractors, when the Customer Satisfaction Score (CSS) attributed to *reliability* is 1 = extremely unsatisfied, 3 = neutral and 5 = very satisfied, at three different scenarios:

Three covariate patterns

- usability = 1, communication =1 and sales = 1 (where 1 = extremely unsatisfied)
- usability = 3, communication =3 and sales = 3 (where 3 = neutral)
- usability = 5, communication =5 and sales = 5 (where 5 = very satisfied)

Bar charts of Adjusted Predictions to evaluated the effect of ***reliability*** at specified covariate patterns

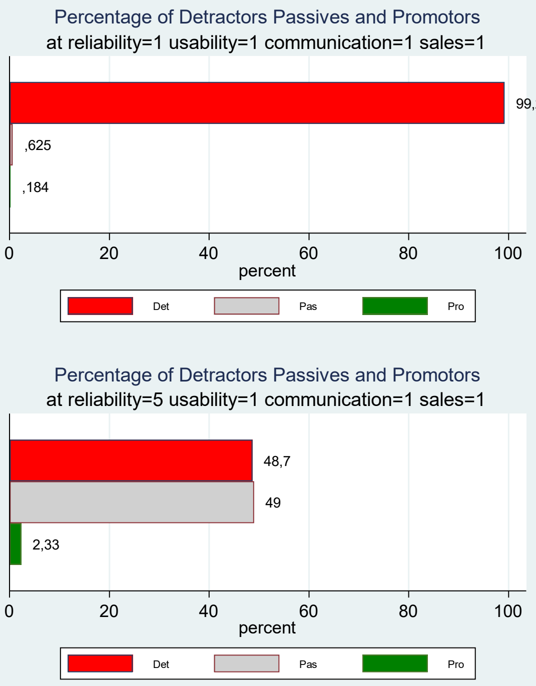


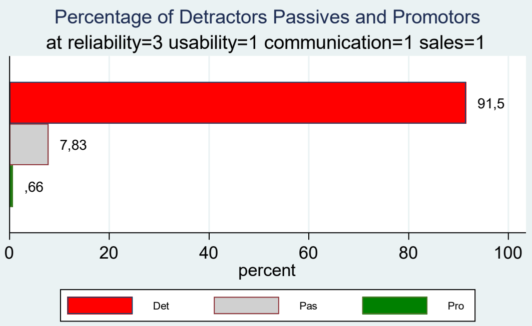
Pattern	
Sales	extremely unsatisfied
Usability	extremely unsatisfied
Reliability	extremely unsatisfied
Communication	extremely unsatisfied

Pattern	
Sales	extremely unsatisfied
Usability	extremely unsatisfied
Reliability	neutral
Communication	extremely unsatisfied

Pattern	
Sales	extremely unsatisfied
Usability	extremely unsatisfied
Reliability	very satisfied
Communication	extremely unsatisfied

Effect of reliability on the Probability to be Detractors Passives and Promotors at usability=1 communication=1 sales=1





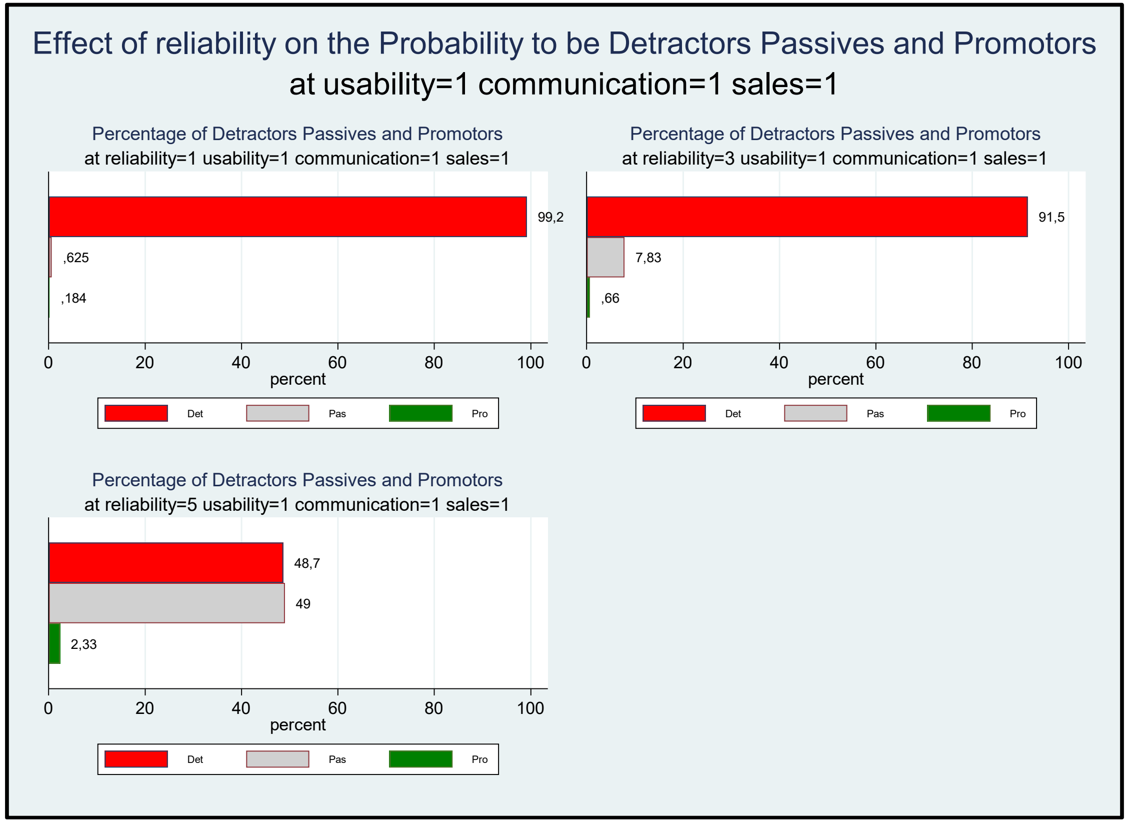
Effects of reliability in a bad scenario

Adjusted Predictions for CS when the CSS attributed to *reliability* moves from 1 = extremely unsatisfied, through 3 = neutral, to 5 = very satisfied, while keeping all the other attributes at the level 1 = extremely unsatisfied

Bar charts of Adjusted Predictions to evaluated the effect of ***reliability*** at specified covariate patterns

Pattern		
Sales		extremely unsatisfied
Usability		extremely unsatisfied
Reliability		extremely unsatisfied
Communication		extremely unsatisfied

Pattern		
Sales		extremely unsatisfied
Usability		extremely unsatisfied
Reliability		very satisfied
Communication		extremely unsatisfied



Pattern		
Sales		extremely unsatisfied
Usability		extremely unsatisfied
Reliability		neutral
Communication		extremely unsatisfied

Effects of reliability in a bad scenario

Adjusted Predictions for CS when the CSS attributed to *reliability* changes, while keeping all the other attributes at the level 1 = extremely unsatisfied

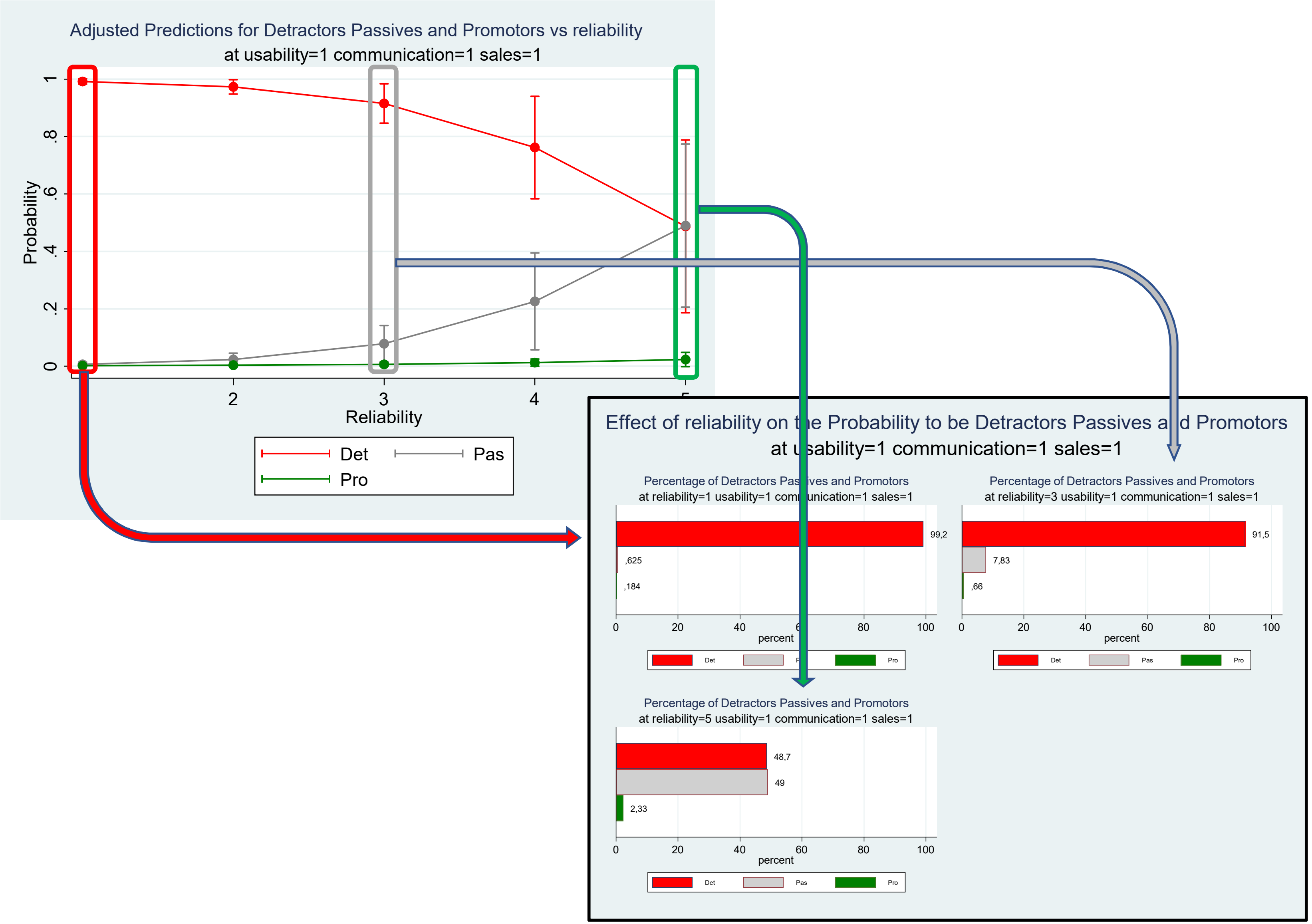
```
. mtable, at(reliability=(1 2 3 4 5) usability=(1) communication=(1) sales=(1))
Expression: Pr(CS), predict(outcome())

           | reliability        1        2        3
-----------+-------------------------------------------
         1 |           1    0.992    0.006    0.002
         2 |           2    0.973    0.023    0.003
         3 |           3    0.915    0.078    0.007
         4 |           4    0.762    0.226    0.012
         5 |           5    0.487    0.490    0.023

Specified values of covariates

           |   sales  usability  communication
-----------+----------------------------------
   Current |       1          1              1
```

Bar charts of Adjusted Predictions to evaluated the effect of ***reliability*** at specified covariate patterns

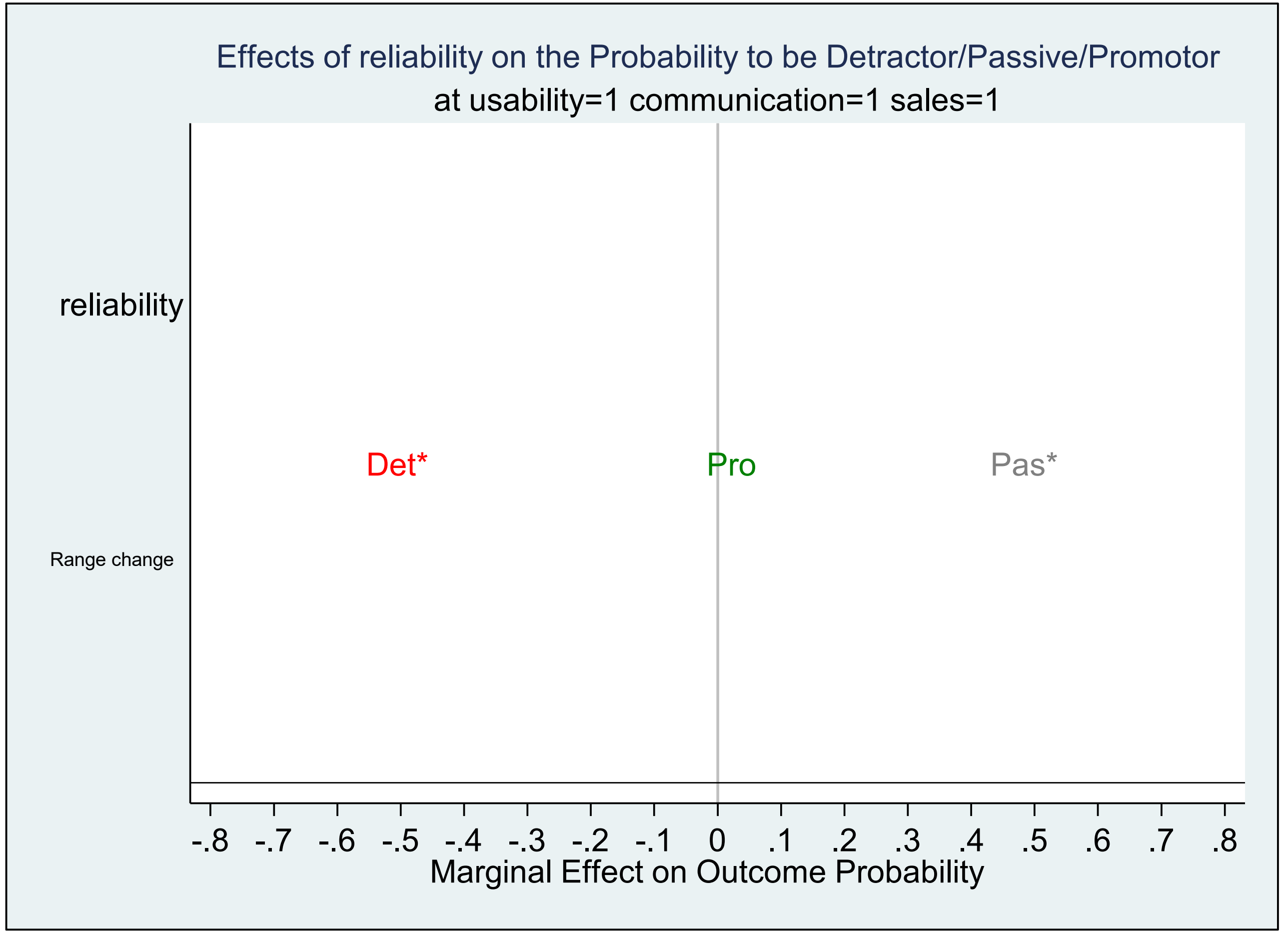


Plot of Marginal Effects of ***reliability*** at specified covariate patterns by *mchange* and *mchangeplot*

. mchange reliability, am(range) at (usability=(1) communication=(1) sales=(1))

	1	2	3
reliability			
Range	-0.505	0.484	0.022
p-value	0.001	0.001	0.075

Good performance on *reliability* can ***prevent customers from spreading bad word-of-mouth*** to their friends and colleagues.



Considerations on the results of the NPS KDA

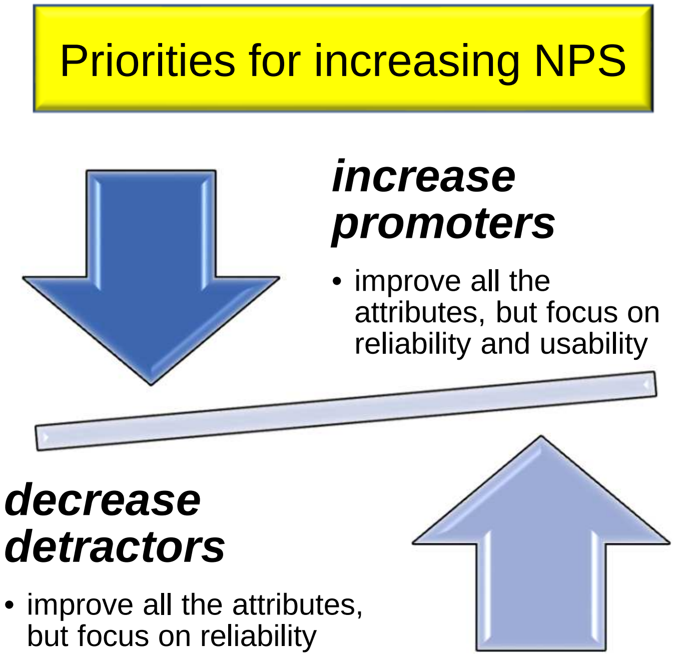
Both the models (**POM** and **PPOM**) allow to investigate the marginal effects of the drivers (significant CX attributes) on promoting customers to a higher level of status, *representing a tool for line managers to design suitable quality improvement strategy*.

The **PPOM** model represents an alternative model to the POM where the proportional odds assumption is violated. Considering that this condition often occurs, the PPOM can be a useful tool for conducting a NPS KDA, which allows line managers to design suitable quality improvement strategies, by ***focusing on those attributes which require the priorities of improvement***.

The **PPOM** allows to identify those facets of product/service which have significant effects on CS, and also ***allows to distinguish the uniform, increasing or decreasing effects*** that each facet of product/service may have on:

- pushing customers away form the pool of detractors
- converting customers into promoters

Results show that three of the significant attributes (***sales***, ***usability*** and ***communication***) have a ***uniform effect*** on improving CS from detractors, through passively satisfied customers, to promoters, while for the attribute ***reliability*** the ***effect on driving customers out of the pool of detractors***, is significantly ***greater*** than its effect on converting customers into promoters, giving evidence of a ***decreasing ability of this facet to improve CS***.



Conclusions

- **Generalized Ordered Regression Models as a tool for implementing NPS KDA**

The Ordered Regression Models represent one of the most common tools for conduction NPS KDA.
NPS KDA allows companies to design suitable improvement strategies based on customer expectations, in order to increase promoters and decrease detractors, so increasing NPS [9].
Reichheld (2006) highlights that reducing the percentage of detractors and increasing the percentage of promoters are two different processes [28], that means that a facet of product/service may not have a uniform effect on moving CS to higher levels.
In such conditions the **PPOM** represents an appropriate tool allowing to investigate the increasing or decreasing effect of an attribute across levels of outcomes [9].

- **The PPOM as an alternative model to the POM to conduct a NPS KDA**

The use of the PPOM as tool for conducting a NPS KDA has been applied in the contest of hotel facility [1] and of online shopping [9].
In this study the **NPS KDA** has been conducted in the contest of the professional audio market, by implementing in Stata two special cases of the Generalized Ordered Logit Models, the Proportional Odds Model (**POM**) and the Partial Proportional Odds Model (**PPOM**), for identifying those drivers which can move CS into higher levels, pulling customers out of the pool of detractors and driving them into the pool of promoters.

- **The PPOM allows to distinguish the uniform, increasing or decreasing effects of each facet of product/service**

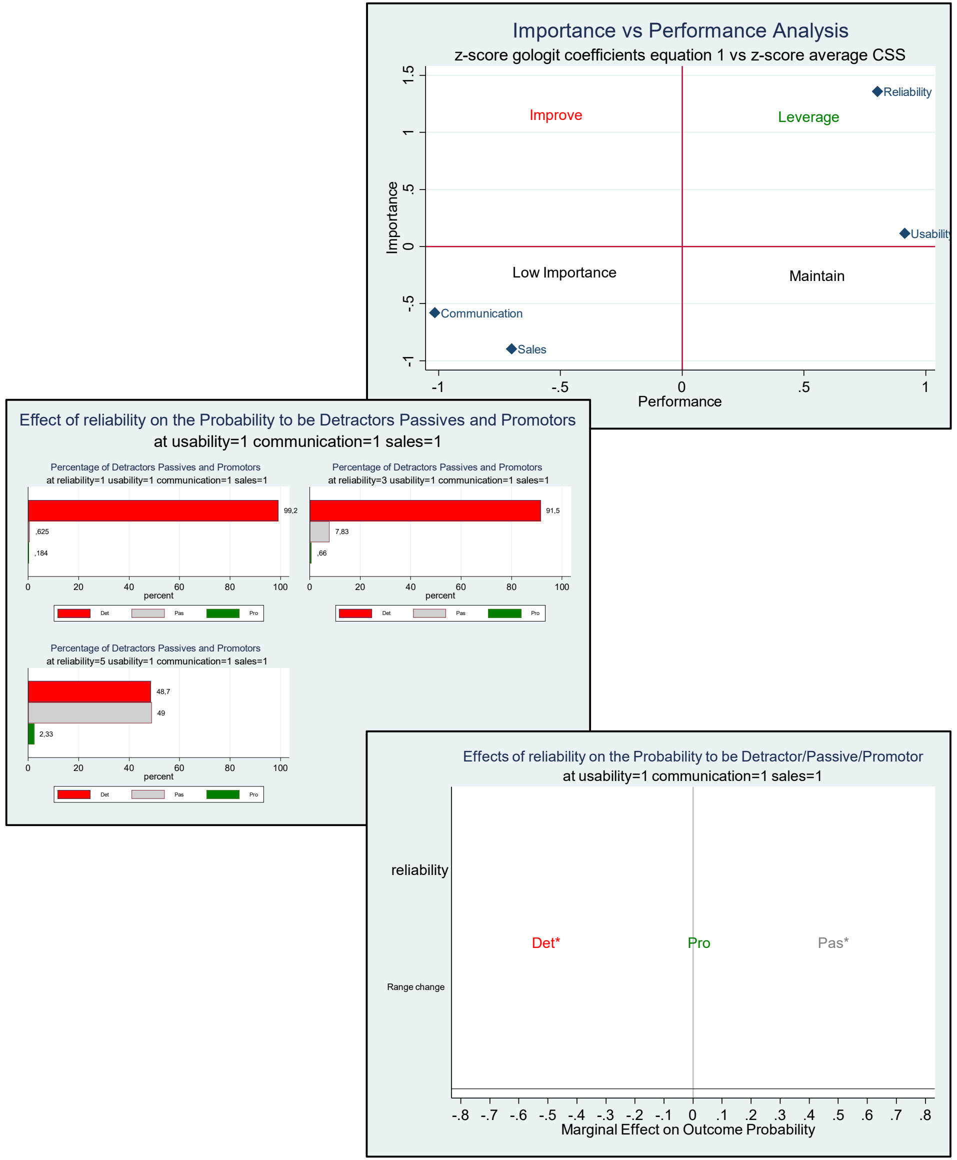
Considering that the proportional odds assumption is often violated, the **PPOM** represents an alternative model which can be used as a tool for conducting a NPS KDA.
This model allows to investigate if some attributes have a greater effect on pushing customers away from the pool of detractors, while others have a greater effect on converting customers into promoters. This information allows line-managers to focus on those attributes which require the priority of improvement and companies to design and develop more focused marketing strategies.

Conclusions

- **Key Drivers' Analysis Reports developed by Stata can support line-managers in interpreting the results**

In this study the **NPS KDA** has been conducted by implementing in Stata two special cases of the Generalized Ordered Logit Models, the Proportional Odds Model (**POM**) and the Partial Proportional Odds Models (**PPOM**), where the dependent variable CS was modelled as function of different CX attributes, in order to explore which facets of product/service have a significant impact on Customer Status, allowing line-managers to take focused improvement actions for increasing Customer loyalty.

Considering that the results of nonlinear model as the POM and the PPOM, are not easy to interpret, especially in a business contest, graphical tool have been developed by Stata, for helping line-managers to interpret the results and design suitable improvement plans.



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Contact & Questions

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Thank You!